

Coupling dynamics of urban flood resilience in china from 2012 to 2022: A network-based approach

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ABSTRACT

Urban flooding presents a significant challenge in Chinese cities, necessitating a deeper understanding of the coupling effects of China's urban flood resilience for effective resilience planning. This study introduces a four-component Environment-Institution-Infrastructure-Agent (EIFA) framework and utilizes an updated correlation network approach to analyze the temporal variation of coupling effects of urban flood resilience across 639 Chinese cities from 2012 to 2022. The findings indicate a decline in synergy and increased tradeoffs, primarily due to intensified competition within and between institutional and infrastructural sectors, marginal impacts of infrastructure investments, and socially excessive infrastructure. The study also highlights the agent component's strong internal and inter-component coupling effects, implying the effectiveness of China's people-centered resilience strategies, though risks of decoupling remain. Additionally, it notes a good match between societal urban flood resilience and natural flood risks, while natural vegetation loss due to urban expansion is noteworthy. The study further suggests that refining agent-focused deposit and insurance policies could coordinatively enhance urban flood resilience, as these elements are hubs within the network. The updated network-based framework and its findings offer insights for informing and optimizing urban flood resilience planning in China.

1. Introduction

Flooding is a major urban disaster worldwide, affecting cities across the globe (Xu et al., 2021). A study by Cao et al. (2022) indicates that from 1985 to 2018, urban expansion significantly increased population exposure to flood risks. Further, it is argued that climate change has exacerbated the severity of urban flooding (Kundzewicz et al., 2013). In response to the augmenting urban flooding challenge, the concept of urban flood resilience was introduced to assess the capacity of urban systems to respond effectively to flooding at various stages (Bertilsson et al., 2019; Sayers et al., 2013). The resilience perspective broadens the scope of flood prevention policies and risk management strategies from a more systematic view (Bertilsson et al., 2019; Xu et al., 2021). The academic understanding of urban flood resilience has evolved over time. Sayers et al. (2013) characterized urban flood resilience through resistance, absorption ability, recovery efficiency, and adaptation capacity

on multiple scales. Xu et al. (2021) describe it in practical terms as the capacity of urban systems to recover from or adapt to flood disasters. Amirzadeh et al. (2022) argue for a broader perspective. They suggest that urban resilience should encompass the full spectrum of urban interactions with disasters and offer a comprehensive definition of general urban resilience. Our study adopts this broad definition and further delineates urban flood resilience as the preparatory, absorptive, recovery, and post-disaster adaptive capacities of an urban area against flood risks.

In addition, recent studies have explored the multifactorial coupling effects in urban flood resilience. These studies analyzed the interactions among stakeholders or resilience factors, which aids policymakers in identifying synergies and tradeoffs (Fenner et al., 2019; Wang et al., 2024; Zhu et al., 2019). In the context of urban flood resilience, coupling effects refer to the interactions between different components of the urban system, such as environment, infrastructure, institutions, and

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agents, that collectively influence resilience outcomes. Synergy effects occur when the interaction between components strengthens resilience, allowing them to work together to improve flood preparedness, response, or recovery. In contrast, tradeoff effects arise when improvements in one component come at the expense of another, limiting the overall capacity to withstand or adapt to flood events (Wang et al., 2024; Zhu et al., 2024). In a city with high flood resilience synergies and low tradeoffs, various components collaborate well and may amplify resilience through interaction. In comparison, cities with high resilience tradeoffs and low synergies have to decide on resource allocation, as resilience cannot be optimized simultaneously. Thus, understanding the coupling effects, including synergy and tradeoff, can improve strategic planning in flooding prevention and better prioritize the development of resilience components (Fenner et al., 2019).

Discussing the multi-component coupling effects within urban flood resilience also necessitates identifying the components involved. Existing literature mainly focuses on the components of urban resilience as a whole rather than on those specific to flood resilience. Therefore, we have adopted the broader classifications of urban resilience components and applied them to the flood resilience context to ensure comprehensive coverage. A general taxonomy by Chelleri (2012) classifies governance structure, physical infrastructure, social networks, and matter-energy flows as key dimensions of urban resilience. Tyler and Moench (2012) introduced a widely applied framework for urban climate resilience that includes urban systems, agents, and institutions. In this framework, urban systems comprise the built and natural environments, agents represent individuals within these systems, and institutions denote the regulatory, legal, and societal frameworks (Tyler & Moench, 2012). Beyond socioeconomic factors, numerous studies emphasize the natural environment as a distinct dimension in flood resilience analysis due to its role in defining inherent flood risk exposure, which is less predictable and controllable compared to other dimensions (Asad et al., 2022; Wang et al., 2021; Yu et al., 2023). Therefore, this study suggests separating the urban system dimension into the natural environment and physical infrastructure to analyze better how anthropogenic and natural elements interact with flood risks. It can avoid the conflation of artificial and natural systems. This leads us to propose the Environment-Institution-Infrastructure-Agent (EIFA) framework to articulate urban flood resilience. The framework is explained in detail in section 2.1, Conceptual Framework.

In China, rapid urbanization has significantly escalated urban flood risks (Tang et al., 2024; Zhang et al., 2016; Zhou et al., 2017). Several studies have assessed the flood resilience of Chinese cities at various scales and have offered developmental recommendations (Lin et al., 2022; Ma et al., 2022; Yang & Wang, 2024; Wang et al., 2021). Nonetheless, investigations into the coupling effects of China's urban flood resilience are limited and have generally focused on regional or city scales with limited temporal spans (Wang et al., 2024; Zhu et al., 2024). Consequently, there is a need for a national-level, long-term analysis to fully understand the temporal variation of these coupling effects, which will serve as a reference for broader-scale resilience planning. In this study, temporal variation of the coupling effects refers to the annual changes in the interactions and relationships between different components or indicators of urban flood resilience.

Concerning methodological approaches, Zhu et al. (2024) applied the coupling coordination degree (CCD) method and spatial correlation models to quantify the coupling effects of urban flood resilience in the Yangtze River Delta. In the broader field of urban resilience, the CCD method and CRITIC-TOPSIS model are widely employed to analyze the existence and strength of the coupling effect in other types of urban resilience (Han et al., 2023; Sun et al., 2024; Xu et al., 2023). Apart from these methods, correlation network analysis has been introduced in recent years to quantify coupling effects in complex systems. A correlation network represents the relationships between variables as nodes connected by edges, where the strength of each connection reflects the correlation between the variables (Felipe-Lucia et al., 2020).

Constructing correlation networks offers a clear visualization and quantification of the coupling effects within complex systems (Wu et al., 2022b). It can use various network metrics to explore system interactions across multiple scales and aspects, providing more perspectives than other methods (Hu et al., 2023; Wu et al., 2022a). For example, Xing et al. (2024) represented the sustainable development goals of China in a correlation network and identified the importance of the goals using link weight and node centrality. In ecology, the correlation network method is applied to evaluate the synergies and tradeoffs among different ecological factors and examine the functionality of an ecosystem (Felipe-Lucia et al., 2020; Hu et al., 2023). Although correlation network approaches are prevalent in ecology and sustainability studies to analyze synergies and trade-offs (Hu et al., 2023; Ings et al., 2009; Wu et al., 2022a), their application in urban flood resilience remains absent. Moreover, this study also identified that the calculation of some metrics can be updated to suit better correlation network analysis, which is detailed in sections 2.5 and 2.6.

To address the gaps mentioned above, this study aims to fulfill three objectives. First, we develop a network-based framework to analyze the temporal variation of coupling effects in urban flood resilience. The framework integrates the Environment-Institution-Infrastructure-Agent subsystems in cities and is expected to be adaptable to other types of urban resilience contexts. Second, the study refines and expands the existing correlation network analysis method to enhance the understanding of synergy and tradeoff effects. Finally, the framework and the updated method are applied to analyze the long-term temporal variation of China's national-level urban flood resilience from 2012 to 2022, thereby informing future resilience planning efforts in China.

2. Material and methods

The flowchart in Fig. 2 provides an overview of this study's workflow. It first constructed a conceptual framework. Then, a correlation network was built based on it. Various network metrics were calculated on network, subnetwork, and node scales. The details of each process are introduced in the following sections.

2.1. Conceptual framework

As outlined in the Introduction section, this study has developed an Environment-Institution-Infrastructure-Agent (EIFA) framework to articulate urban flood resilience. In the EIFA framework, every component consists of multiple factors or indicators reflecting the strength of flood resilience in the corresponding component of an urban area. The environmental component includes the natural factors that directly lead to or constrain flooding events, reflecting the topographical, hydrological, ecological, and meteorological attributes that physically influence the local water cycle. These factors, considered largely unaffected by human activity in the short term, represent the natural flood exposure of the city's region.

The infrastructure component specifically refers to physical structures that influence flood preparedness, resistance, or recovery (Chelleri, 2012). Indicators in this component quantify aspects such as scale, volume, coverage, and density of infrastructure. Meanwhile, the institution component, as expanded from the work of Tyler and Moench (2012), consists of non-physical indicators representing socio-economic conditions, policies, governmental investment, and public service capabilities related to flood management and recovery at the city level. The agent component captures demographic attributes, financial status, education, information accessibility, and insurance coverage at the individual level.

Further, this study operationalized the EIFA concept using a network-based framework. In this framework, the system of Chinese urban flood resilience is represented as a network, where each component (environment, institution, infrastructure, agent) is represented as a subnetwork. Each subnetwork has various nodes, which are the related

indicators of urban flood resilience. The synergy effects among nodes and subnetworks, including synergies and tradeoffs, are represented by links. The weight of each link reflects the magnitude of the interaction. This framework allows us to assess the temporal variation and dynamic interactions between different resilience factors over time, providing a comprehensive view of how urban flood resilience is shaped by both socio-economic and environmental factors. The sample city selection, indicator selection, construction of the network, and analysis of the network are elaborated in sections 2.2 to 2.7.

2.2. Study area

Numerous cities across China are threatened by floods originating from multiple sources. Between 2000 and 2019, approximately 400 flooding events were reported, affecting around 900 million people (Ma et al., 2022). Specifically, from 2008 to 2010, floods impacted 62 % of Chinese cities, with over 180 cities facing annual flood threats (Tang et al., 2024; Zhang et al., 2016). China's urban regions, characterized by high population densities and significant economic concentrations, are reported to experience more severe flood impacts compared to rural areas (Zhang et al., 2016). Additionally, climate change projections indicate increased frequency and intensity of extreme precipitation events across China, including in semi-arid and arid regions, thereby escalating overall urban flood risks (Liang et al., 2019). Rapid urbanization also contributes to increased flood susceptibility by expanding impervious surfaces, which may lead to larger flood inundation areas (Luo & Zhang, 2022; Su et al., 2014).

Given the widespread nature of China's flood risks, this study encompasses a broad analysis covering most Chinese cities rather than focusing on specific locations. The study period spans from 2012 to 2022. Hence, our study provides extensive spatial and temporal coverage to comprehensively explore the multi-component coupling effects of urban flood resilience in China.

Data limitations necessitated the exclusion of some cities. Specifically, cities that had too many data gaps, were newly established, or had changes in administrative status during the study period were omitted to

maintain data consistency. The study incorporates data from 639 (92 %) of the extant cities across mainland China, including 4 direct-administered municipalities (provincial-level cities), 293 prefecture-level cities, and 342 county-level cities. These cities are indicated as blue spots in Fig. 1. The wide spatial coverage and the high sample-population ratio bolster data representativeness.

It is important to note that in China, the provincial, prefecture, and county levels represent the three highest subnational administrative divisions. Cities may fall within any of these levels, and lower administrative divisions such as townships and villages are not classified as cities (Central People's Government of the People's Republic of China, 2009). The administrative boundaries of county-level cities typically align with their physical urban areas, excluding townships and villages. Conversely, the boundaries of direct-administered municipalities and prefecture-level cities might encompass various lower-level settlements, with their physical urban areas designated as municipal districts (National Bureau of Statistics of China, 2023). For our analysis, we utilized city-level data for county-level cities and selected data exclusively from municipal districts for direct-administered municipalities and prefecture-level cities to ensure a focus on actual urban extents and maintain consistency in scale across the study.

Current studies focused on direct-administered municipalities and prefecture-level cities only (Han et al., 2023; Sun et al., 2024; Wang et al., 2024; Zhu et al., 2024). Nevertheless, as another major component of Chinese urbanization, county-level cities, though with full urban functions and dense populations (Li, 2011), are always ignored, leading to a lack of research on their risk resilience. Therefore, by integrating county-level data, we also expanded the current scope of urban flood resilience studies in China to include all levels of cities and provide a more comprehensive analysis.

2.3. Indicator selection and pre-processing

To apply the conceptual framework to real-world scenarios, it is essential to carefully select specific indicators for each component. This study identified city-level numeric indicators through systematic

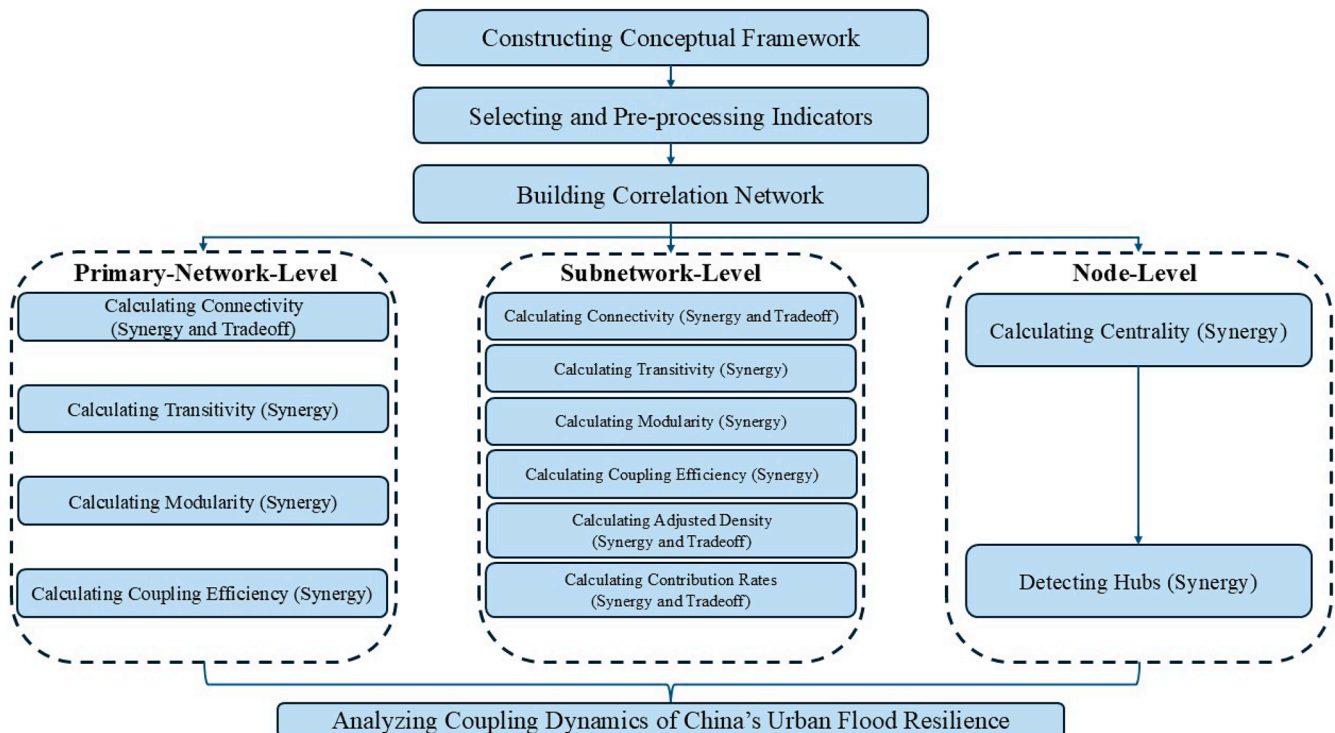


Fig. 1. The workflow of this study.

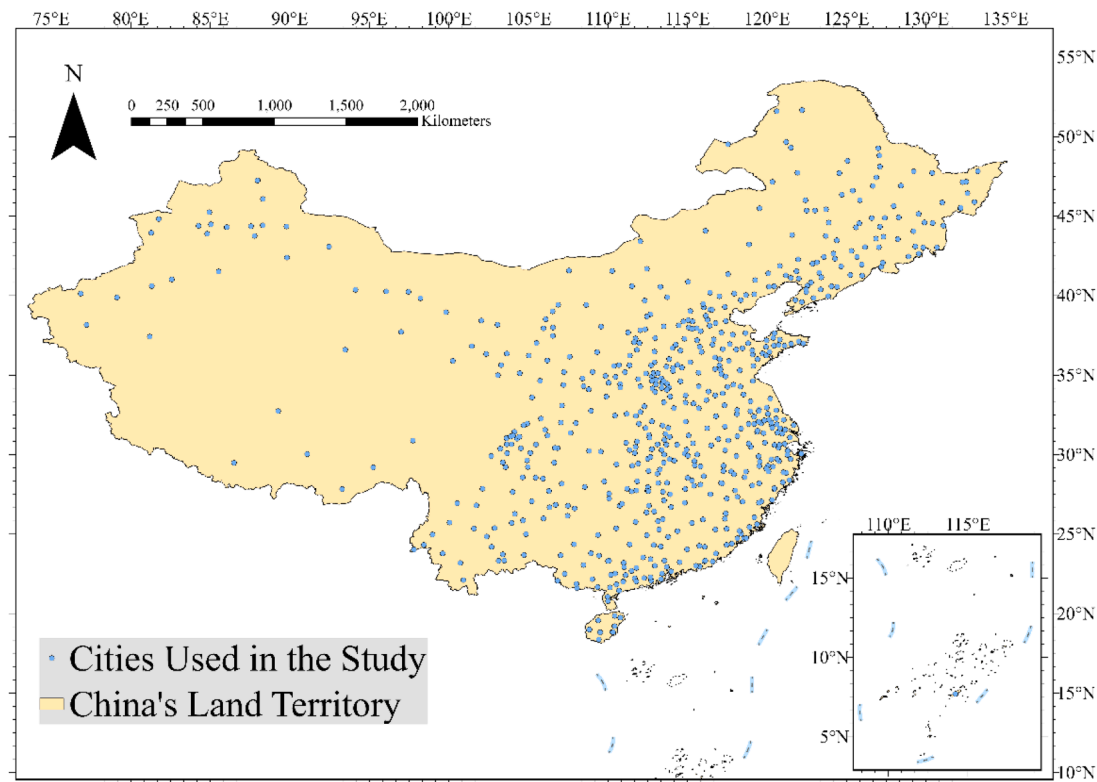


Fig. 2. Study area and the cities involved in the study.

literature review and expert justification. The initial screening criteria for these indicators required their presence in at least two studies, availability of source data in over half of the sample cities, and data spanning at least five years within the study period. The criterion requiring indicators to appear in at least two studies ensures that they are academically meaningful, generalizable, and not limited to specific cases, thus increasing their relevance to our national-scale analysis. The threshold for data availability in over half of the sample cities ensures a statistically reliable sample size for inter-indicator correlation, enhancing the robustness and confidence of the coupling effects and further comparison (Kraemer & Blasey, 2015). Additionally, requiring at least five years of data helps maintain consistency, allowing for more credible interpolation of missing data and supporting more reliable inter-annual comparisons (Faraway, 2002). Detailed criteria for each component's indicators are based on the definition of each component in section 2.1 and outlined in Table 1. We tried to utilize raw datasets from specific domains without aggregating them, ensuring our research maintains a high level of detail. As a result, over 160 indicators were initially available. Subsequently, the shortlisted indicators were evaluated by urban flood resilience experts to ensure their representativeness and to eliminate redundancy. Representativeness was assessed by examining that the indicators were applicable across diverse urban

environments in China, accounting for variations in geography, population density, and flood infrastructure. To eliminate redundancy, the experts applied hierarchical clustering methods to group similar indicators, retaining only those that captured distinct aspects of urban flood resilience. Cross-validation among the three experts from three research institutions was applied to enhance objectivity and consistency in the final indicator selection. After this process, 55 indicators were selected for this study. All final selected indicators have been validated through both comprehensive literature support and expert review, ensuring their relevance and reliability for the intended analysis

Notably, instead of focusing on flood-specific indicators only, we chose a broad set of indicators to capture the complexity of urban systems and their relevance in flood resilience research. By integrating flood-specific and broad-resilience indicators, the analysis can better reveal the coupling effects and trade-offs among different resilience factors within urban systems. This approach not only considers direct flood resilience but also captures the complexity of urban systems. It better aligns with the suggestion of McClymont et al. (2020), who advocate for embracing complexity rather than simplifying systems in flood resilience research.

The indicator system was developed through a systematic literature review, a three-round screening process, and expert validation, making

Table 1
Component-specific indicator selection criteria.

Component Name	Criteria				
	Scale	Temporal Coverage	Indicators' Functions	Does it reflect physical objects?	Is it natural or social-related?
Environment	City	2012-2022	Directly causing or limiting floodings	Yes	Natural-related
Institution	City	2012-2022	Regulating flood risk planning, absorption, recovery, or adaptation	No	Social-related
Infrastructure	City and Individual	2012-2022	Achieving flood risk planning, absorption, recovery, or adaptation	Yes	Social-related
Agent	Individual	2012-2022	Influencing personal flood risk preparation, absorption, recovery, or adaptation	Not specified	Social-related

it a robust matrix for evaluating flood resilience. Due to the specific criteria explained above, some potentially related indicators were not included. However, alternative indicators addressing similar domains were integrated into this framework and have been thoroughly supported by literature and expert input. In the future, as more data, particularly city- and county-level data, becomes available, the scalability and inter-comparability of our network analysis method will allow for the seamless integration of new data, enabling updated insights over time.

Linear interpolation was employed for handling missing data (Huang et al., 2024). The interpolated data were then normalized relative to population, area, or gross economic measures to adjust for city size variations. After pre-processing, each indicator was assigned an ID. The finalized set of the 55 indicators, along with their assigned IDs, are listed in Table 2. To enhance readability and maintain consistency throughout the paper, subsequent sections, and figures refer to these indicators by their IDs rather than their full names. The unit, explanation of the relationship to urban flood resilience, pre-processing methodology, and references for each selected indicator are detailed in Table S1 in the Supplementary Material.

The datasets for infrastructure, institution, and agent components were derived from the China City Statistical Yearbook and China Urban Construction Statistical Yearbook covering 2013 to 2023, which report data from the preceding years (National Bureau of Statistics of China, 2013-2023; Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2013-2023). Specifically, for the four selected environmental indicators, only the values of the vegetation coverage in non-built-up areas were extracted from the China Urban Construction Statistical Yearbooks. The source data of the other three

environmental indicators is provided by remote sensing products, including ALOS World 3D—30m digital elevation model product (Japan Aerospace Exploration Agency, 2021), MERIT Hydro: Global Hydrography Datasets (Yamazaki et al., 2019), and PERSIANN-CDR (Ashouri et al., 2015; Sorooshian, 2014). The remote sensing data was processed using Google Earth Engine.

2.4. Coupling network construction

Compared with other methods for evaluating coupling effects, network analysis can intuitively visualize the coupling effects and provide more metrics to quantify various aspects of the coupling effects. A coupling network is a type of correlation network used to represent an interconnected system. In this network, nodes represent objects that have coupling effects on each other, while links indicate the presence of these effects. The weight of each link corresponds to the magnitude of the coupling effect between the nodes. Thus, we chose to apply a network-based approach to conduct the analysis of coupling effects. Based on the EIFA framework, we first designed a four-component conceptual network to quantify the coupling effects of China's urban flood resilience, as displayed in Fig. 3. This network visualizes the four components as distinct subnetworks, where each node represents an indicator of a specific aspect of urban flood resilience. The links, which are the synonyms of connections or edges, between nodes denote the presence and intensity of coupling effects. These links can signify either synergies or tradeoffs between indicators. Links within a subnetwork represent interactions within a single resilience component, while those between subnetworks reflect the coupling effects across different components.

This study adapts the concept of correlation network to operationalize the conceptual network in Fig. 3 and constructs urban flood resilience coupling networks. In these networks, nodes represent indicators, and the strength of their correlation indicates the weight of the links between them. Consequently, the weight of a link reflects the coupling strength between two connected indicators. The coupling strength in our study refers to the magnitude of coupling effects between any pair of urban flood resilience indicators, components, or within the whole coupling network. To ensure unit consistency and prevent measurement scales from influencing correlation strength, all indicators were normalized to a range between 0 and 1 using Min-max normalization (Wu et al., 2022b). To align the direction of indicator impacts, we applied a $(1-x)$ transformation to indicators that are posited to negatively affect flood resilience, including E2, E3, E4, I11, I18, F8, F13, A1, and A6. This adjustment ensures that higher indicator values universally signify a positive contribution to flood resilience (Felipe-Lucia et al., 2020; King et al., 2024).

Spearman correlation analysis was performed on each pair of scaled indicators to determine the strength of their relationships every year. Following the approach of Wu et al. (2022b), the absolute value of the correlation coefficient was used to define the link weights in the coupling network. Positive and negative correlation coefficients were separately used to construct networks representing synergistic and tradeoff relationships, respectively. Given that correlations do not specify the direction of influence, all networks were designed as undirected (Felipe-Lucia et al., 2020).

To ensure the relevance and statistical significance of the connections, links with an absolute correlation coefficient below 0.1 or a significance level above 0.1 were excluded. Autocorrelation was also addressed by removing connections identified through collinearity analysis (Wu et al., 2022b). All nodes were retained in the network regardless of their connectivity to maintain network size consistency and facilitate longitudinal comparisons. All network analysis and visualization were conducted using the NetworkX 3.3 package in Python (Hagberg et al., 2008).

Table 3 lists all network metrics and related terms used in this study with corresponding explanations, the levels at which they are applied,

Table 2
The selected indicators and IDs.

Component Type	Indicators and IDs
Environment	Vegetation coverage in non-built-up area (E1), Blue spot coverage (E2), River network density (E3), Maximum monthly precipitation of the year (E4).
Institution	Investment proportion in water supply (I1), Investment proportion in transportation infrastructure (I2), Investment proportion in drainage (I3), Investment proportion in sewage treatment (I4), Investment proportion in water recycling (I5), Investment proportion in urban greening (I6), Investment proportion in environmental sanitation (I7), Investment proportion in waste treatment (I8), Investment completion rate (I9), Per capita gross regional product (I10), Primary industry growth contribution (I11), Secondary industry growth contribution (I12), Tertiary industry growth contribution (I13), Gross regional product growth rate (I14), Average Profit of Industrial enterprises (I15), Proportion of fiscal expenditure on science (I16), Proportion of fiscal expenditure on education (I17), Annual fiscal deficit (I18), Teacher-student ratio (I19), Physician-population ratio (I20).
Infrastructure	Water supply coverage (F1), Water supply pipeline density (F2), Per capita transportation land use area (F3), Drainage pipeline density (F4), Sewage treatment rate (F5), Greening rate in built-up areas (F6), Domestic waste treatment rate (F7), Impervious surface coverage (F8), Per capita residential land area (F9), Logistics and warehousing land use ratio (F10), Per capita sidewalk area (F11), Road density (F12), Overwater bridge-road ratio (F13), Per capita daily sewage treatment capacity (F14), Road cleaning and sanitation frequency (F15), Per capita waste treatment capacity (F16), School-population ratio (F17), Per capita hospital bed count (F18), Per capita road freight volume (F19).
Agent	Population density (A1), Urbanization rate of the population (A2), Proportion of registered residents (A3), Average wage of employees (A4), Per capita retail sales (A5), Per capita loan balance (A6), Per capita deposit balance (A7), Per capita library book holdings (A8), Mobile phone subscription rate (A9), Pension insurance coverage (A10), Medical insurance coverage (A11), Unemployment insurance coverage (A12).

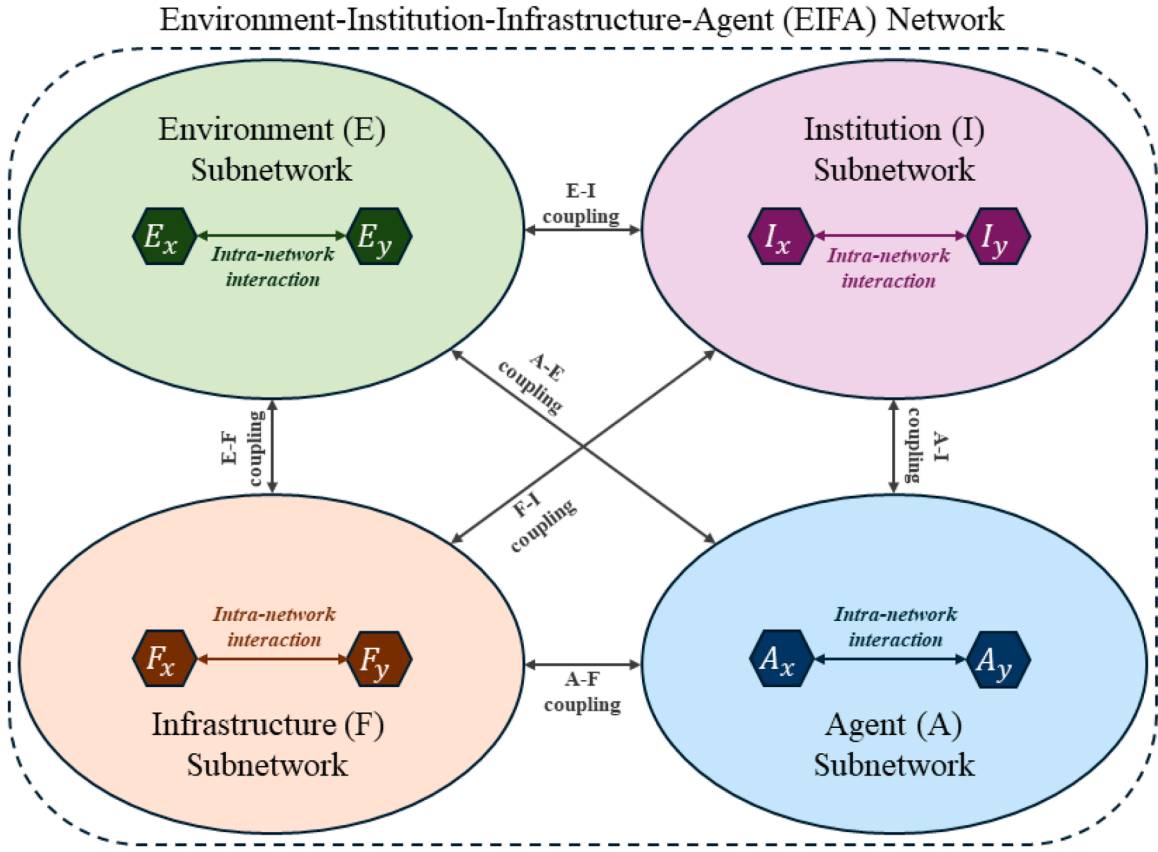


Fig. 3. Conceptualized network based on the EIFA framework.

and references. Sections 2.5, 2.6, and 2.7 introduced the belonging process and calculation methods of these metrics. Specifically, the coupling efficiency, adjusted density, and contribution rate are newly developed by us to cope with the issues in existing network analysis applications or expand the scope.

2.5. Primary Network Analysis

For the study period from 2012 to 2022, we established eleven annual correlation networks, referred to as primary networks. These networks encompass both synergy and tradeoff connections. In our visualizations, only the primary networks are displayed, with separate metrics computed for the synergy and tradeoff networks. Initially, we assessed connectivity for both types of links each year, measuring the global strength of these effects relative to the maximum potential total link weight in a network with an equivalent number of nodes (Wu et al., 2022b). Additionally, we computed transitivity, modularity, and efficiency, which respectively illuminate the localized coupling effect, the robustness of group divisions, and the ease with which coupling effects propagate throughout the network. These calculations were conducted solely for the synergy network due to the complexities involved in interpreting these measures for the tradeoff network (Felipe-Lucia et al., 2020).

As for efficiency, a classical calculation for efficiency in a weighted network is to get the average of the reciprocals of the shortest path lengths between all node pairs, as shown in Equation 1 (Deng et al., 2012; Latora & Marchiori, 2003).

For a network G:

$$E = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d(i, j)} \quad (1)$$

where:

E denotes the network's overall efficiency.

n is the total number of nodes in the network.

$d(i, j) = \min(\sum_{e \in G} w_e)$. Namely, $d(i, j)$ represents the shortest weighted path between nodes i and j .

w_e is the weight of an existing edge e .

Nevertheless, the implications of weight in correlation networks differ from those in the classical calculation. In the correlation networks, a higher correlation-derived weight indicates a stronger connection and a more effective impact transmission. Thus, the calculation in Equation 1 can be misleading as it assumes higher weights indicate greater physical distances or barriers in transmission (Latora & Marchiori, 2003). Some studies have responded to this challenge by converting the network to an unweighted format for simpler efficiency calculation (Wu et al., 2022a; Yuan et al., 2021). However, we proposed a modified efficiency calculation tailored for correlational coupling networks, where higher weights signify a beneficial effect on information transformation, as Equation 2 presents.

For a network G:

$$\text{Coupling } E = \frac{t_{ideal}}{t_{observed}} = \frac{n(n-1)}{\sum \min\left(\sum_{i \neq j \in G} \frac{1}{w_{ij}}\right)} \quad (2)$$

where:

Coupling E represents the overall efficiency of a correlation-derived coupling network.

t_{ideal} is the shortest possible time required to traverse all points, assuming each pair of nodes is directly connected with a weight of 1, reflecting optimal connectivity.

$t_{observed}$ is the observed shortest time required to traverse all points in the network.

Table 3

Network terms and metrics used in the study.

Metrics	Definition	Usage in the Study	Applied level(s)	References
Synergy Link	The connection between two indicators that have a positive significant Spearman correlation coefficient.	It implied the two connected indicators have a synergy effect (able to reach higher values simultaneously) in urban flood resilience.	Primary network and Subnetwork	Felipe-Lucia et al., 2020; Xing et al., 2024
Tradeoff Link	The connection between two indicators that have a negative significant Spearman correlation coefficient.	It implied the two connected indicators have a tradeoff effect (unable to reach higher values simultaneously) on urban flood resilience.	Primary network and Subnetwork	Felipe-Lucia et al., 2020; Xing et al., 2024
Node Count	Number of nodes in a network, reflecting the network size.	It represents the number of indicators in the corresponding primary network or subnetworks.	Primary network	Hu et al., 2023; Wu et al., 2022a
Link Count	Number of links in a network.	It represents the number of synergy and tradeoff relationships in the primary network or subnetworks.	Primary network	Hu et al., 2023; Wu et al., 2022a
Link Weight	A typically positive value reflecting the connection strength of a link.	This study uses the absolute value of the Spearman correlation coefficient between two indicators as the weight of their link, ranging from 0 to 1.	Primary network and Subnetwork	Felipe-Lucia et al., 2020; Wu et al., 2022b
Connectivity	The proportion of the observed total link weight to the maximum possible total link weight with nodes unchanged.	It can reveal the overall coupling strength of the given network.	Primary network and Subnetwork	Wu et al., 2022b
Transitivity	Also known as the global clustering coefficient. It is defined as the ratio of the total number of triangles in the network to the number of possible triangles. In network analysis, a triangle refers to a set of three nodes that are all directly connected to each other by links.	It is used to reflect the local-level coupling effects of a network.	Primary network and Subnetwork	Hu et al., 2023; Wu et al., 2022a
Modularity	The strength of a network's division into modules (also called communities or clusters). High modularity indicates a structure where there are dense connections between the nodes within modules but sparse connections between nodes in different modules.	It is used to reflect the evenness of the distribution of the coupling effects across the network.	Primary network and Subnetwork	Wu et al., 2022b
Coupling Efficiency	Updated by this study based on the common network efficiency calculation. The ratio of the shortest possible traversal time in the network when all nodes are connected with a link whose weight is 1 to the observed traversal time. In the calculation, the weight is defined as the speed of the effect to pass between the two connected nodes. The distance for time calculation is defined by the adjacency matrix.	It quantifies how effectively the variation of a source indicator can be transmitted throughout the network through the coupling effects. It is used to replace traditional efficiency calculation.	Primary network and Subnetwork	Latora & Marchiori, 2003; Yuan et al., 2021
Eigenvector Centrality	A measure of a node's influence within a network, calculated based on the centrality of its neighbours and its own connections. A higher value indicates that the node is more important in the network.	In this study, it is used to rank the importance of the indicators and find hubs.	Node	Bonacich, 1987
Hubs	Nodes with high eigenvector centrality values. They serve as central points that link many other nodes within the network.	Hubs are defined in the synergy network with the top three highest eigenvector centrality values each year. It reveals the indicators that can maximize the synergy effect to develop urban flood resilience.	Node	Hu et al., 2023; Xing et al., 2024
Adjusted Density	Updated by this study based on the density (connectivity) calculation. The ratio of the observed inter-subnetwork link weight to the maximum possible inter-subnetwork link weight with node count and distribution unchanged.	It can quantify the synergy and tradeoff strength between two components (subnetworks). The normalization enables comparison among the subnetwork pairs with different node numbers and distribution types.	Subnetwork	Bartsch et al., 2015; Bedru et al., 2020
Contribution Rate	Developed by this study. The ratio of the inter-annual change in the weight of a particular link type to the total change in link weight across the entire network for the corresponding year. It can identify the direction and the magnitude of one link type's contribution to the overall temporal variation of the coupling network.	It helps detect the major contributors to the overall temporal variation of the coupling network.	Subnetwork	N/A

n is the total number of nodes in the network.

w_{ij} is the weight of an existing link between two connected nodes i and j .

This method provides a more intuitive approach to assessing efficiency within correlation networks. Latora and Marchiori (2003) traditionally defined weights as the physical distance between nodes. In contrast, in our study, weights represent the tightness of the connection between two indicators, which we interpret as the speed at which the coupling effect is transmitted from the source node to the target node. Given that there are no intermediary nodes between any pair of directly connected nodes, we define the distance as 1. This value mirrors the adjacency matrix value Latora and Marchiori (2003) used to define topographical step size. Consequently, the transmission time for the effect between any two connected nodes is calculated as $1/w$. To determine the shortest transmission time across the network, we employed Dijkstra's algorithm in the NetworkX 3.3 package of Python to

find the path between any two nodes that minimizes the transmission time and then aggregated these minimum times to compute $t_{observed}$. We then introduced t_{ideal} to normalize the time measurements for cross-network efficiency comparisons. The ideal scenario, t_{ideal} , is achieved when every pair of nodes is connected by a link with the maximum possible weight of 1, as determined by the maximum possible value of the Spearman correlation coefficient.

The metric *Coupling E* quantifies the proportional difference between the existing network traversal time, $t_{observed}$, and the optimized traversal time, t_{ideal} . As this metric increases, the efficiency of traversing all nodes in the network improves, indicating a more optimized network configuration. This formulation of coupling efficiency offers a more straightforward and intuitive understanding of how effectively coupling effects are transmitted across a correlation network. Additionally, we choose the concept of time rather than average speed because efficiency calculation should avoid biases associated with using arithmetic means for approximation, as Latora and Marchiori (2003) highlighted.

2.6. Subnetwork-level analysis

2.6.1. Subnetwork segmentation and internal attributes quantification

While existing research on correlation networks typically emphasizes node-level and global coupling effects (Hu et al., 2023; Ings et al., 2009; Wu et al., 2022b), our study extends this approach to examine the implications at the subnetwork scale. As depicted in Fig. 3, the primary coupling network is segmented into four distinct subnetworks: environment, institution, infrastructure, and agent. Same as the primary network, we calculated connectivity for both synergy and tradeoff connections in each subnetwork. Transitivity, modularity, and coupling efficiency were computed exclusively for the synergy parts to facilitate more unambiguous interpretation. During this analysis, all links between different subnetworks were disregarded.

Furthermore, we chose not to analyze the metrics of environmental subnetwork in detail for two key reasons. First, only four environmental indicators directly related to flooding were included, which limits their ability to represent the broader environmental context fully. Second, as discussed in the Introduction and the Conceptual Framework sections, urban flood resilience primarily focuses on the proactive capacity of societal structures in responding to disasters. The role of the environmental subnetwork in this study is to examine how socio-economic factors interact with the natural environment rather than analyzing the environment's internal variations independently. Therefore, the temporal variation within the environmental subnetwork was not the primary focus of this study and is excluded from further analysis.

2.6.2. Analysis of inter-subnetwork coupling effects

In addition to exploring the internal temporal variation within individual components, this study also examines the inter-component coupling effects, as represented by the inter-subnetwork links. These links are categorized into six groups based on the connected nodes' IDs: Agent-Institution (A-I), Agent-Environment (A-E), Agent-Infrastructure (A-F), Institution-Environment (I-E), and Institution-Infrastructure (I-F). For this analysis, we focused exclusively on inter-subnetwork links, disregarding all intra-subnetwork connections.

Previous studies have limited focus on quantifying the strength of connections at the subnetwork level. Bartsch et al. (2015) measured the total link weight between conceptualized organ networks to indicate the strength of inter-organ physiological connections. However, this approach is only effective for comparison if the subnetworks are of similar size or if the nodes comprehensively represent all network constituents. In cases where these conditions are not met, a different measure is needed to account for variations in node counts and distributions across different pairs of connected subnetworks.

Typical network size-normalized indicators, such as average degree and density, are not suitable for our analysis since intra-subnetwork links are intentionally omitted, resulting in a network structure that we refer to as "amputated." This structure contains only inter-subnetwork links, reducing the number of possible links compared to those accounted for in traditional density calculations, which should have been $n(n-1)$.

To address this issue, we revised the approach to calculating network density metrics by introducing an adjusted weighted density. This new metric normalizes the strength of inter-subnetwork links to enable comparisons across different node sizes and distributions. The rationale is that, in two amputated subnetworks g_i and g_j , where the intra-subnetwork connections are forbidden, the maximum possible link count equals the maximum number of links connecting heterogeneous nodes. It is the number of nodes in g_i multiplying the node number of g_j . As aforementioned, the maximum possible link weight calculated by Spearman correlation is 1. Thus, the maximum possible total link weight equals the maximum link count. The resulting metric, calculated for both synergy and tradeoff networks, is defined in Equation 3.

For subnetworks g_i and g_j :

$$\text{adjusted } D_{(g_i, g_j)} = \frac{\text{observed } W_{(g_i, g_j)}}{\text{ideal } W_{(g_i, g_j)}} = \frac{\sum_{i \in g_i, j \in g_j} w_{ij}}{n_{g_i} \times n_{g_j}} \quad (3)$$

where:

$\text{observed } W_{(g_i, g_j)}$ is the observed total link weight between g_i and g_j .

$\text{ideal } W_{(g_i, g_j)}$ is the maximum possible total link weight between g_i and g_j , assuming no change in node count and distribution.

$\text{adjusted } D_{(g_i, g_j)}$ is the adjusted weighted density for the subnetwork links between g_i and g_j .

n_{g_i} and n_{g_j} are the numbers of nodes in the two subnetworks separately.

w_{ij} is the weight of any inter-subnetwork link between g_i and g_j .

2.6.3. Contribution rates calculation for link's temporal variation

This study further explores the contribution of various link types to the temporal variation within the primary network. Although it reflects contributions to the overall changes in the primary network, we still assigned this part under subnetwork-level analysis. This is because it involves the calculation of various link types, which inherently represent the types of internal and inter-subnetwork coupling described in sections 2.6.1 and 2.6.2. Given that the primary network and its subnetworks maintain a constant number of nodes annually, variations in the network metrics are solely attributable to changes in link weights and distributions. To measure the impact of specific types of links on the overall network's temporal variability, we analyzed the ratio of the inter-annual change in the weight of a particular link type to the total change in link weight across the entire network for the corresponding year.

Links are categorized based on the subnetworks (E, I, F, or A) of their connected nodes into ten types: EE, II, FF, AA, EI, EF, EA, IF, IA, and FA. For a comprehensive analysis, we calculated the inter-annual change in total link weight for each link type within both the synergy and tradeoff networks. The contribution rate of each link type is then determined by dividing this value by the overall change in link weights across the synergy or tradeoff network. This calculation is formalized in Equation 4. This approach allows for a detailed understanding of how different types of interactions within the flood resilience network contribute to its evolution over time. It can reveal the roles that specific link types play in the network's temporal variation.

For link type x in year n :

$$\text{Contribution}_{x_n} = \frac{\sum w_{x_n} - \sum w_{x_{(n-1)}}}{\sum w_{\text{primary network}_n} - \sum w_{\text{primary network}_{(n-1)}}} \quad (4)$$

where:

$\text{Contribution}_{x_n}$ is the contribution rate of link type x to the overall link variation in year n .

w_{x_n} is the weight of any link belonging to link type x in year n .

$w_{\text{primary network}_n}$ is the weight of any link in the primary network in year n .

2.7. Node-level analysis

In the node-level analysis, we calculated the eigenvector centrality values for all nodes within the synergy network and ranked them accordingly. Nodes exhibiting higher eigenvector centrality are considered key influencers, as this measure indicates that the targeted node is well connected to other important nodes within the network (Bonacich, 1987). We refrained from identifying hubs in the tradeoff network due to the complexities associated with interpreting the broader implications of their second-order or more distant connections.

The nodes with the top three highest eigenvector centrality values

were identified as hubs in each annual network. This hub detection process enables decision-makers to gain insights into the pivotal roles of specific factors within the network. Understanding these key nodes facilitates more focused policy interventions and helps target hubs to leverage their significant influence, which may enhance policy outcomes through the propagation of dense synergy effects (Xing et al., 2024).

3. Results

3.1. Temporal variation of the primary urban flood resilience coupling network

Fig. 4 presents the annual primary Agent-Institution-Infrastructure-Environment (EIFA) coupling networks in 2012, 2015, and 2022. The network visualization for all years from 2012 to 2022 can be found in Figure S1 in the Supplementary Material. Each network comprises 55 nodes that represent indicators across the four resilience components. Throughout the study period, each indicator maintained at least one connection annually, illustrating pervasive inter-indicator coupling effects within the EIFA network. The number of links, or edges, varied annually. It dropped slightly from 799 in 2012 to 795 in 2017, then decreased notably to 751 in 2022. This trend implies decreasing coupling effects of Chinese urban flood resilience.

Fig. 5 analyzes multiple network attributes to quantify the temporal variation of the coupling effects from 2012 to 2022. It provides connectivity measures for both synergy and tradeoff networks, while transitivity, modularity, and efficiency are calculated solely for the synergy network.

According to Fig. 5(a), the connectivity of the synergy network has shown a consistently decreasing trend from 2013, with the highest value at 0.091 in 2013, declining to 0.075 by 2022. Conversely, as shown in Fig. 5(b), the tradeoff network's connectivity experienced a decrease from 0.051 in 2012 to 0.048 in 2019, followed by a rebound to above 0.052 in 2022. Compared with the synergy network, the variation range of the tradeoff network is much smaller, indicating a more stable temporal pattern. Generally, the connectivity of the tradeoff network is consistently lower than the synergy network. It reflects that synergy effects are denser and dominant over tradeoff effects in Chinese urban flood resilience systems during the study period. However, with the increase of the former and the decrease of the latter after 2019, the gap has been narrowed.

The transitivity of the synergy network, as illustrated in Fig. 5(c), also shows a decreasing trend, although the range of change is limited to less than 0.086. The average transitivity remains high, signifying frequent local-scale interactions among triads of nodes. This metric, unaffected by link weight, also suggests that while the number of links is high, the weights of these links are relatively low within the synergy

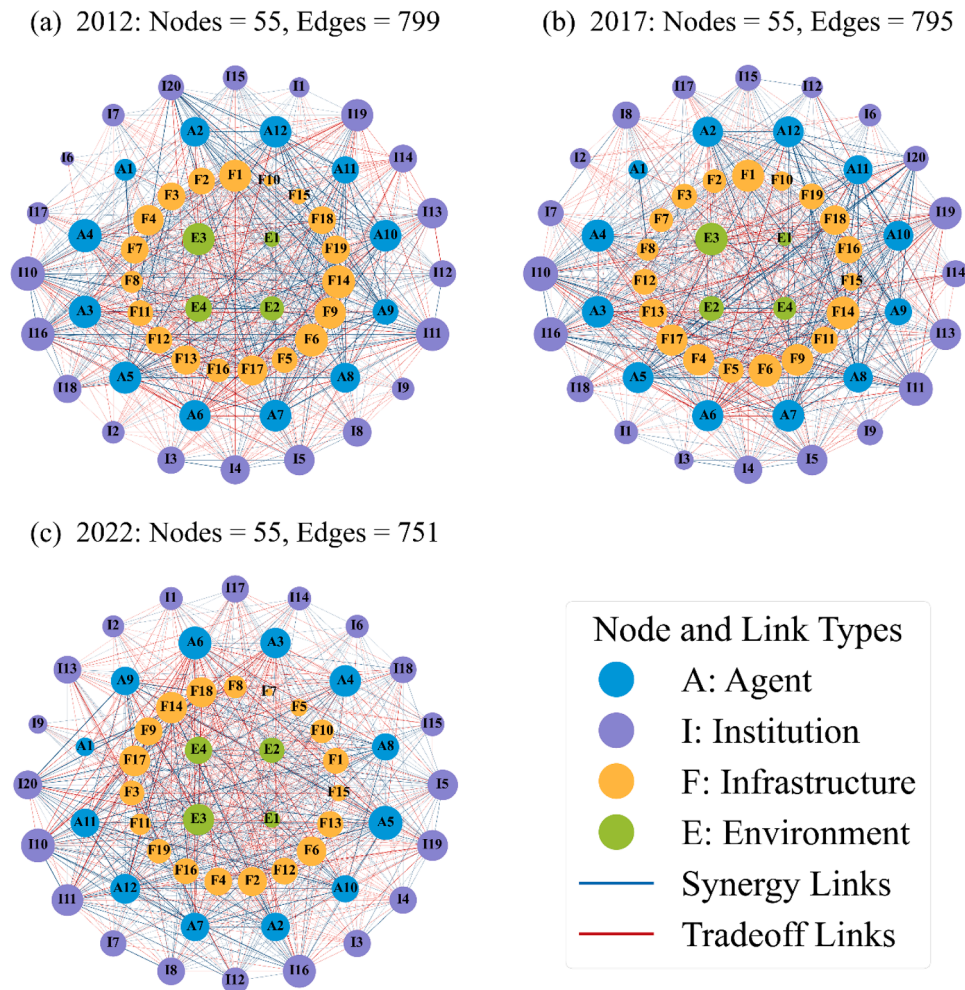


Fig. 4. Agent-Institution-Infrastructure-Environment (EIFA) network for every five years. The Shells network layout was applied to distinguish between components. (a), (b) and (c) are the annual primary coupling networks in 2012, 2017, and 2022. Nodes from the same resilience component have the same colour. Blue links indicate synergy, while red links are tradeoff connections. The size of the nodes represents the total weights of the links connecting to them, and the width of the edges represents their weights.

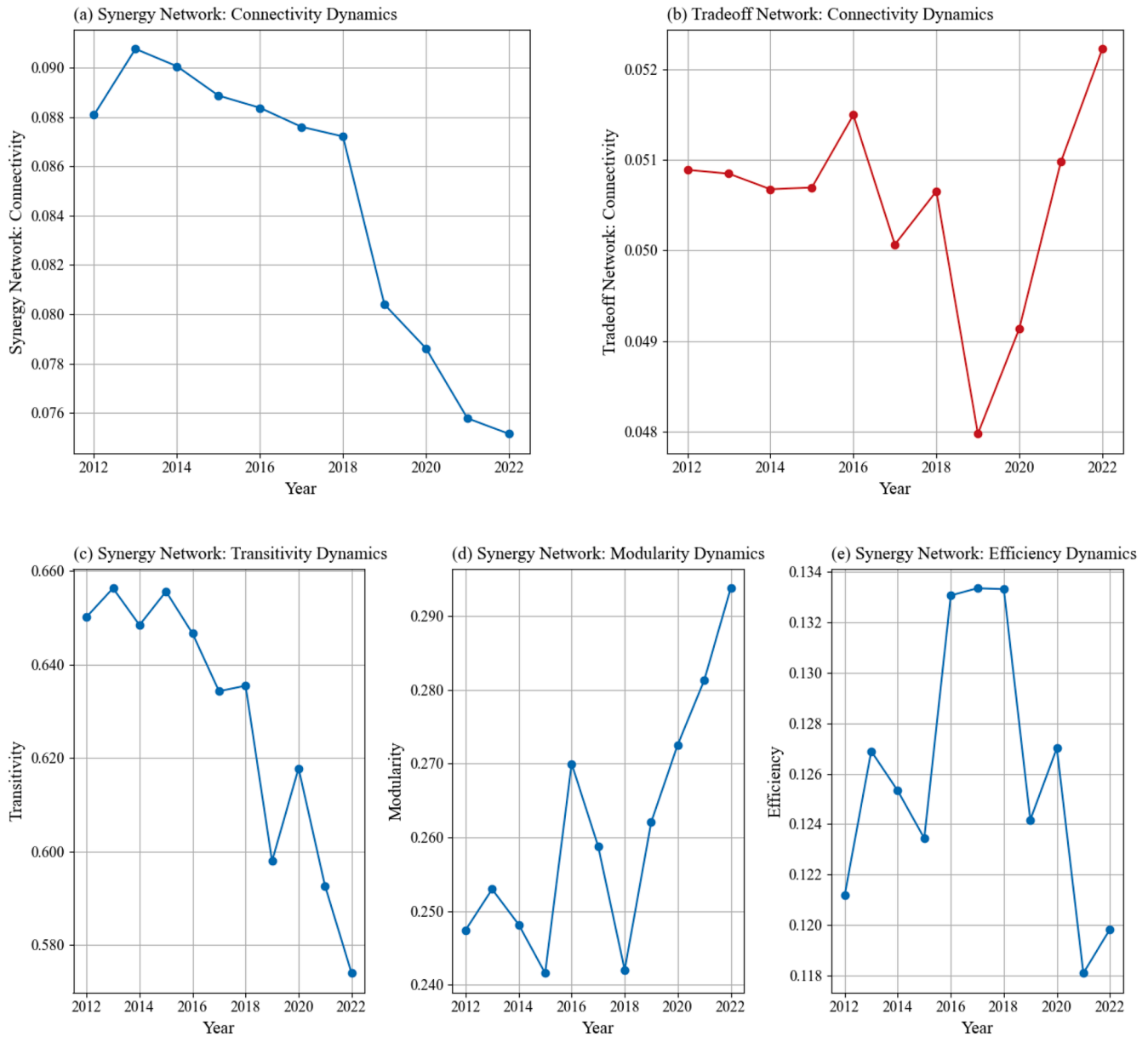


Fig. 5. Attributes' temporal variation of the synergy and tradeoff networks from 2012 to 2022. (a)-(b) shows the connectivity for both synergy and tradeoff networks separately. (c)-(e) illustrates the transitivity, modularity, and efficiency of the synergy network only because these metrics are difficult to interpret in the tradeoff network.

network. Combined with the connectivity trend, we suggest that both the overall and local level coupling effects have a relatively high level of synergy effects, but the effects are weakening to a degree over time. The increasing modularity from 2018 to 2022, detailed in Fig. 5(d), indicates a growing unevenness in link distribution among nodes. At the same time, this attribute is lower than 0.3 throughout the study period. The trend of modularity reveals that the synergy effects evenly exist in the Chinese urban flood resilience system, while the evenness is subtly decreasing. Finally, Fig. 5(e) outlines the temporal variation of the efficiency, which peaked at approximately 0.133 before 2017 and then declined, reaching its lowest point of 0.118 in 2021. The fluctuations in efficiency have been confined to a narrow range over the past decade, indicating that the efficiency for the synergy effect to be conducted on the whole urban flood resilience system in China is relatively low and does not change significantly during the study period.

3.2. Coupling strength within and among subnetworks

3.2.1. Temporal variation of internal attributes of subnetworks

Fig. 6 illustrates the temporal variation of various internal attributes of the agent, infrastructure, and institution subnetworks from 2012 to 2022. It presents connectivity data for both synergy and tradeoff networks, while other attributes are analyzed exclusively within the synergy subnetwork due to the complexities associated with interpreting these metrics in the tradeoff context.

Fig. 6 (a) and Fig. 6 (b) reveal that the agent subnetwork consistently shows the highest connectivity among the subnetworks in both synergy and tradeoff contexts, albeit with slight fluctuations. The connectivity of the infrastructure subnetwork in the synergy network is slightly higher than that of the institution subnetwork. However, in the tradeoff network, the connectivity of the infrastructure subnetwork is marginally lower than that of the institution subnetwork. Nonetheless, both the infrastructure and institution subnetworks have significantly lower

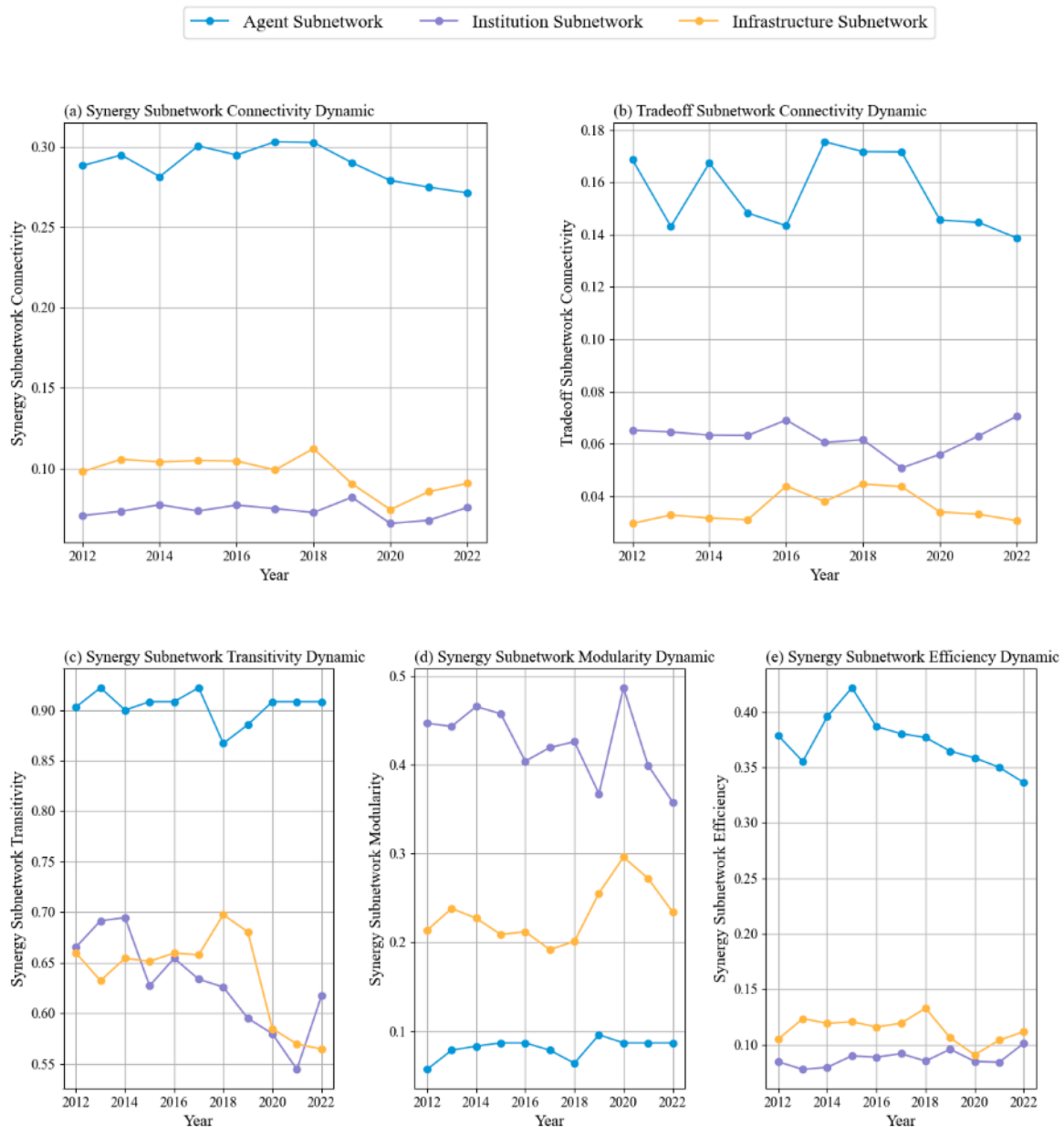


Fig. 6. Temporal variation of subnetwork attributes from 2012 to 2022. (a) and (b) display the connectivity trends for the subnetworks in synergy and tradeoff networks, respectively. (c)–(e) focus on the transitivity, modularity, and efficiency of the subnetworks within the synergy network.

connectivity values compared to the agent subnetwork. It is also noted that synergy connectivity substantially exceeds tradeoff connectivity for all three subnetworks. These observations reflect that the agent component of Chinese urban flood resilience has the strongest coupling effect, especially on the synergy side, and the synergy effects of the three socio-economic flood resilience components are all stronger than the tradeoff effects.

In the synergy network, Fig. 6 (c) indicates that the agent subnetwork maintains exceptionally high and stable transitivity, contrasting sharply with the lower transitivity observed in the institution and infrastructure networks. Both latter networks exhibit decreasing trends over time. It further reinforces the finding that the agent component has the most robust synergy effects among the three studies' subnetworks.

As shown in Fig. 6 (d), the agent network exhibits the lowest level of modularity, which has slightly increased after 2018. The infrastructure subnetwork displays a medium level of modularity, while the institution network records the highest modularity, averaging over 0.4. These

values imply that the distribution of the synergy effect in the agent component is the most equal, while the institution component has the most uneven coupling effect distribution.

Fig. 6 (e) reflects similar trends to those seen in connectivity: the agent network possesses the highest efficiency, which shows a slight decline after 2015. The infrastructure network and the institution network consistently demonstrate significantly lower efficiency values throughout the study period. Moreover, the differences in efficiency between the infrastructure and institution networks are relatively narrow. The comparison of the efficiency reveals that the agent component of the urban flood resilience has the highest speed for the synergy effects to be conducted, but the speed shows a decreasing trend during the study period.

3.2.2. Inter-subnetwork temporal variation of coupling effects

Fig. 7 visualizes the temporal variation of adjusted density, which quantifies the strength and yearly variations of inter-subnetwork

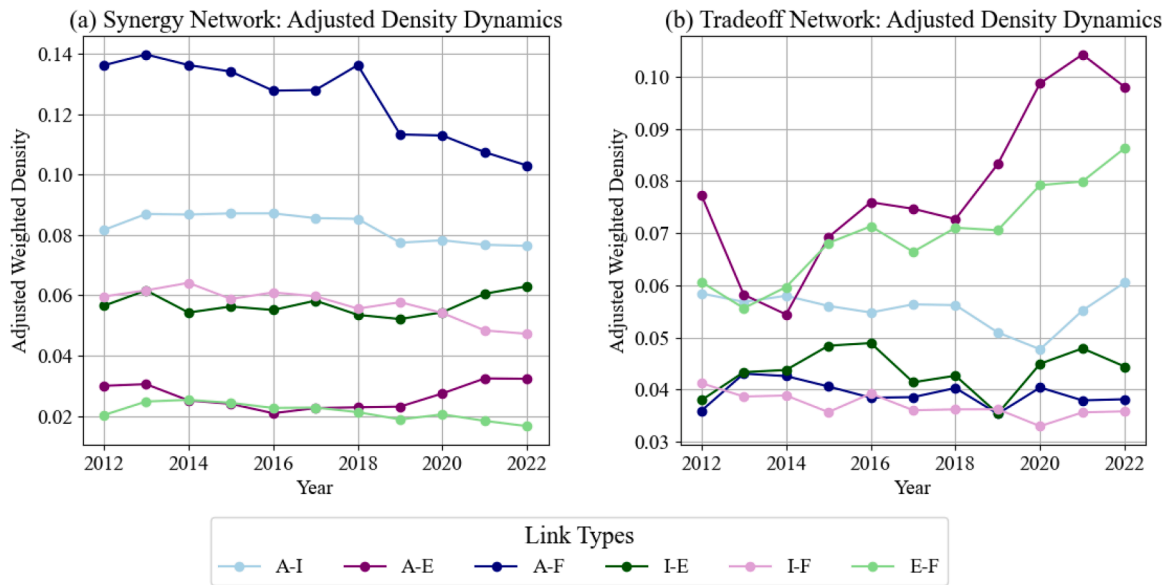


Fig. 7. Adjusted density's temporal variation of the four inter-subnetwork link types. (a) and (b) show the adjusted density variations for subnetworks in synergy and tradeoff networks separately. The adjusted density accounts for differences in network size and node distribution, facilitating more accurate comparisons of coupling strength among different link types.

coupling.

In the synergy network, as Fig. 7 (a) demonstrates, most link types exhibit stable adjusted densities over time. The density of the Agent-Infrastructure (A-F) link type shows a noticeable decrease while remaining the highest each year. Following this, the densities of Agent-Institution (A-I) and Institution-Infrastructure (I-F) are also relatively high but slightly dropped at the same time. In comparison, Agent-Environment (A-E) and Environment-Infrastructure (E-F) link types consistently display the lowest adjusted density values, indicating weaker inter-subnetwork synergy. Additionally, the Institution-Environment (I-E) connections also show one of the lowest densities from 2012 to 2020. The low density of A-E, E-F, and I-E connections suggests relatively weak inter-subnetwork synergy strength in the environment subnetwork. Our study argues that this is a positive trend and discusses it in section 4.2.2 in detail.

The tradeoff network, as shown in Fig. 7 (b), presents a contrasting pattern. Notably, the link types with the highest adjusted densities (A-E and E-F) in the tradeoff network are the same ones that have the lowest densities in the synergy network, and these densities exhibit an upward trend in tradeoff density. It aligns with the low synergy density of the A-E and E-F links, collectively suggesting an increasing risk-resilience matching, which is also discussed in section 4.2.2.

3.2.3. Contribution of edge types to the temporal variation of the primary network

Fig. 8 uses two heatmaps to illustrate the contribution of each link type on the overall inter-annual link changes in the synergy and the tradeoff networks.

The contribution of each link type to network changes is complex, as indicated in Fig. 8. No single link type consistently contributes positively or negatively throughout the study period. According to Fig. 8 (a), the mean contribution rankings reveal that both outbound and internal links of the infrastructure network generally positively influence the overall variability of the synergy network. In contrast, the internal links of the environment subnetwork and links connecting to it often exhibit changes that contradict the general trend of the synergy network.

In the tradeoff network, as shown in Fig. 8 (b), a distinctive pattern emerges where the internal connections within the environment, infrastructure, and agent subnetworks tend to contribute less significantly or even negatively to the overall change in link weights. Conversely,

internal links of the institution subnetwork more frequently exert a substantially positive influence on the overall network variation. These results can help us better understand the causes of the overall variation of the coupling effects in the Chinese flood resilience system. They are referenced in section 4.1 to explain the observed temporal variations.

3.3. Annual shifts of network nodes

Fig. 9 depicts the hubs within the synergy network for each year, highlighting nodes that consistently acted as central connectors. Being designated as a hub indicates that a node is well-connected to other important nodes through dense connections. Notably, all identified hubs originate from the agent subnetwork. Throughout the decade, nodes A7 (Per capita deposit balance) and A12 (Unemployment insurance coverage) consistently emerged as hubs in the synergy network every year. Node A11 (Medical insurance coverage) was frequently a hub as well, with the exceptions of 2012 and 2014 when Node A5 (Per capita retail sales) took its place. This further suggests that the agent component plays a key role in understanding and optimizing the coupling effects of Chinese urban flood resilience. The implications are discussed in section 4.3.

Fig. 10 provides a visualization of all nodes' rankings within the synergy network based on their eigenvector centrality, offering a comprehensive view of the temporal variation of each node's importance. The rankings demonstrate general stability over time, with most nodes consistently appearing either in the higher or lower echelons of the ranking spectrum. This stability corroborates the limited variation in hub identity observed in Fig. 9, indicating that the core influencers within the network have remained relatively unchanged.

4. Discussion

4.1. Primary network level: noteworthy decoupling trends of synergy

The correlation network approach provides a clear reflection of the coupling effects of urban flood resilience across various dimensions. It offers advantages over the widely used Coupling Coordination Degree (CCD) method in its ability to automatically distinguish between synergy and tradeoff through positive and negative correlations without the need to define a threshold for continuous values artificially (Dong et al.,

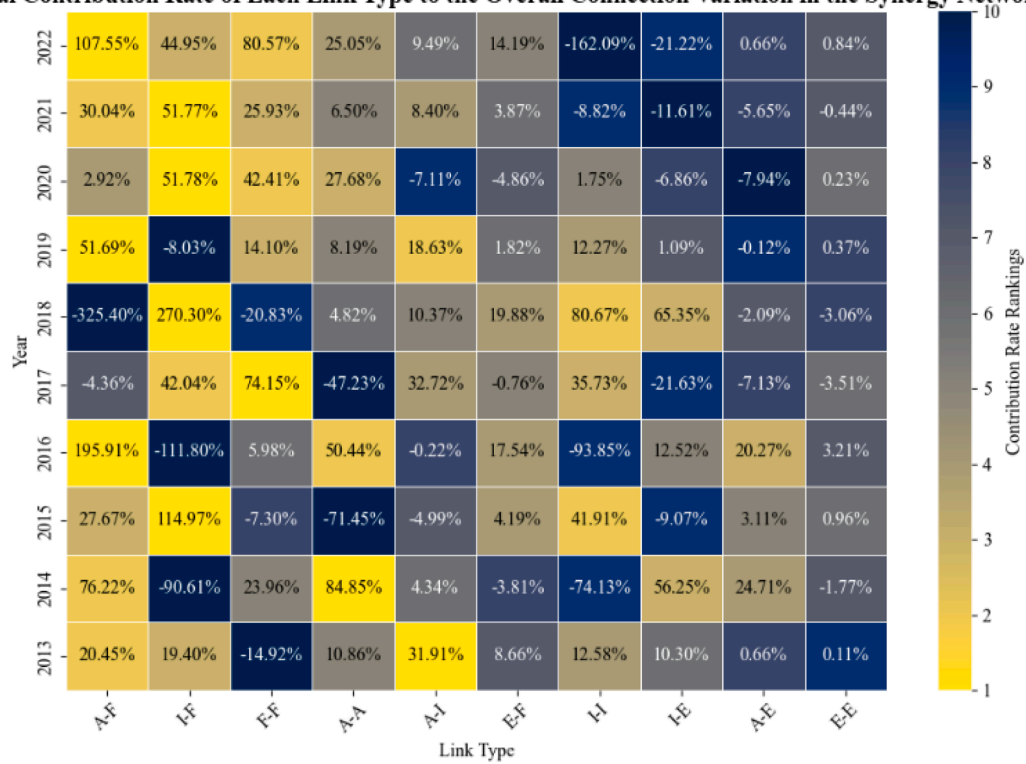
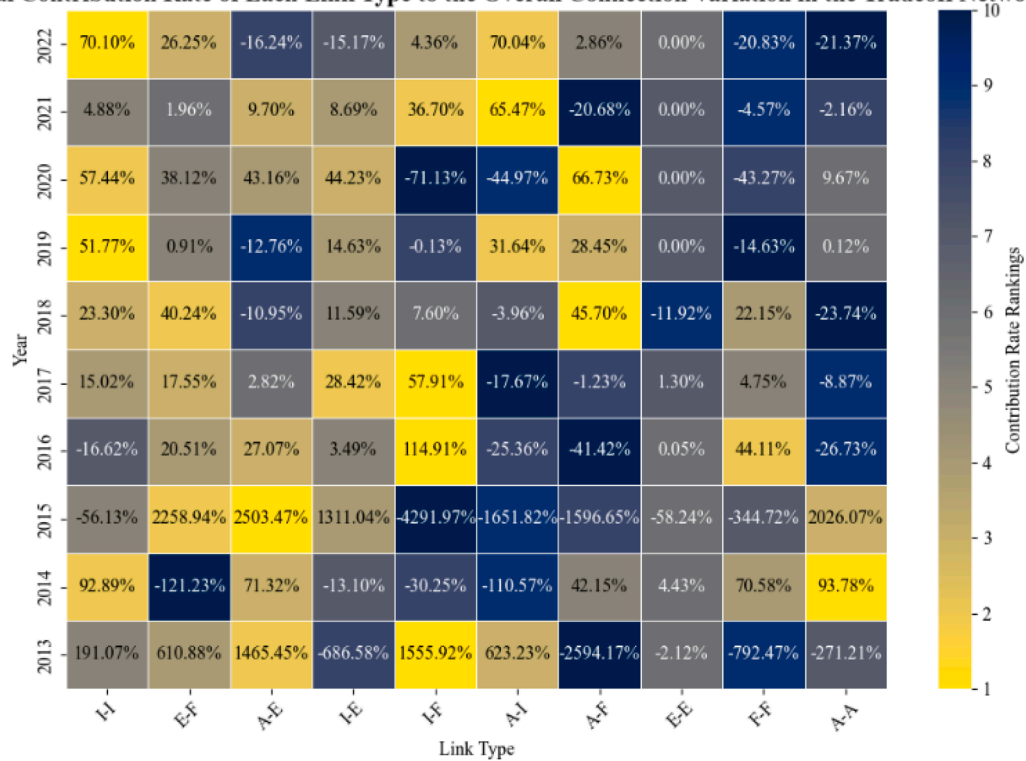
(a) Annual Contribution Rate of Each Link Type to the Overall Connection Variation in the Synergy Network**(b) Annual Contribution Rate of Each Link Type to the Overall Connection Variation in the Tradeoff Network**

Fig. 8. Annual contribution rate of weighted edge count by edge type. (a) shows the rankings of synergy links. (b) shows the node rankings of tradeoff links. The link types are ordered using their average ranking from left to right. Link types with higher rankings are filled with brighter colours, while the ones with lower rankings have darker colours. The annotation on each grid reflects the actual contribution rate of that link type to the gross change in link counts. The positive or negative rates do not indicate the increase or decrease of the actual counts; instead, a positive rate indicates that the count change of the link type is in the same direction as the gross change. A negative one means the changing directions are opposite.

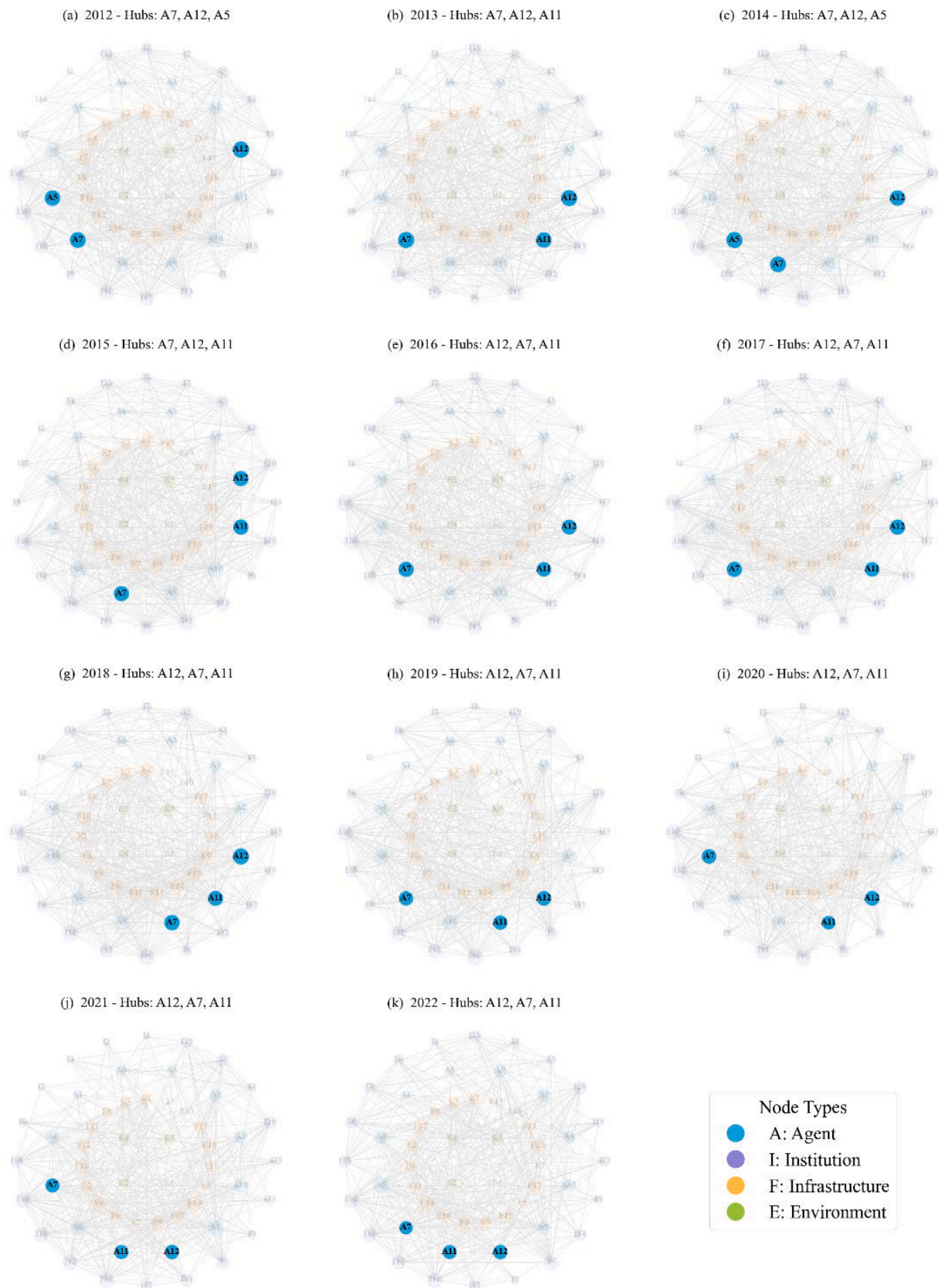


Fig. 9. Each year's synergy hubs, defined by the nodes with the top three highest eigenvector centrality. (a)-(k) are the annual primary coupling networks from 2012 to 2022, with the hubs highlighted. In the title of each year's network, the hubs are ranked from the highest eigenvector centrality from left to right. The size of the nodes represents the total weights of the links connecting to them.

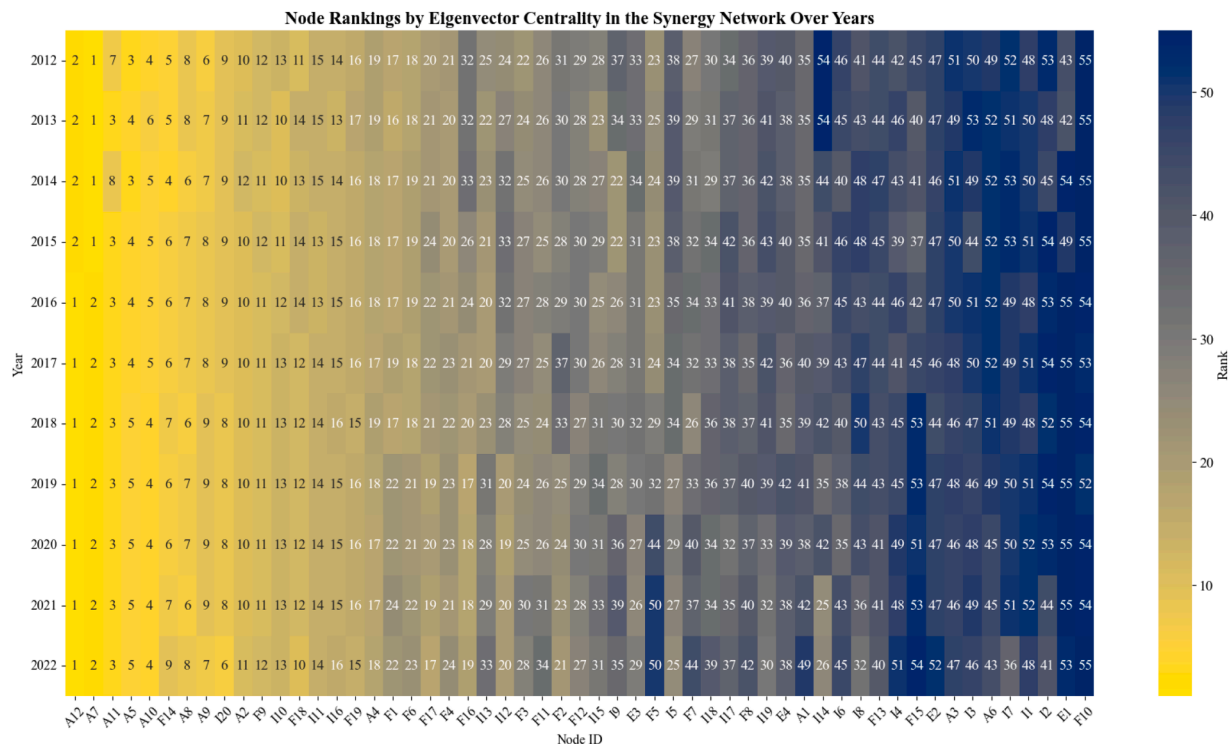


Fig. 10. Rankings of each node by eigenvector centrality in the synergy network from 2012 to 2022. In descending order, it arranges nodes from left to right based on their average rankings over the study period. Nodes with higher rankings are highlighted in brighter colours, while those with lower rankings are in darker colours, visually representing their centrality and importance within the network.

2023; Xing et al., 2024).

By examining the connectivity of the synergy and tradeoff networks, as shown in Fig. 5 (a) and Fig. 5 (b), it is apparent that synergy effects are generally more pronounced than tradeoff effects. Nevertheless, Chinese cities have witnessed a notable decrease in overall synergy and an increase in the tradeoff effects from 2019 to 2022. In a more intuitive sense, the percentage of the total weight to the maximum possible weight in the synergy network decreased from 9.1 % to 7.5 %, and in the tradeoff network, it increased from 4.8 % to 5.2 %. Coordination is weakening, and conflicting interests or competitive interactions are more prominent in shaping urban flood resilience strategies during urban development. Additionally, Figs. 4 (c), 4 (d), and 4 (e) indicate a decrease in transitivity, modularity, and efficiency of the synergy network after 2018. It signals a decline in local coupling strength and the speed of effect transmission, with sectors becoming more segregated by small groups. This observation may be partially attributed to the COVID-19 pandemic, which disrupted the coordination of operations in urban areas. The decreasing urban flood resilience synergies may result in less effective flood response and recovery. One example is the flooding disaster in Zhengzhou City, China, which was caused by extreme precipitation in 2021. According to the official investigation report, one factor that intensified the flood damage was the city’s inadequate coordinative flood response mechanism (Xinhua News Agency, 2022). Additionally, in 2021, the General Office of the State Council of China (2021) mentioned that the coordinative flood management was inadequate in Chinese cities. The document suggested that the cities of China should “coordinate development and safety and consider the city as an organic living entity to address urban waterlogging issues through coordinated approaches and systematic methods.” (General Office of the State Council of China, 2021, p.1). Our study reinforces this argument.

We also analyzed factors contributing to the observed trends. According to Fig. 8, the reductions in institution-infrastructure, agent-infrastructure, and intra-infrastructure synergies are generally the primary drivers behind the weakening synergy strength after 2018. In

contrast, the increase in intra-institution tradeoff is the key contributor to the strengthening tradeoff after 2019. The declining internal and external synergy and the rising external tradeoffs of the infrastructure components may be pivotal driving factors of the overall synergy decrease and tradeoff increase.

The increasing tradeoff and decreasing synergy of internal coupling of infrastructure and institution components can be attributed to the allocation of governmental financial resources. As urban areas grow, the demand for financial resources to enhance flood resilience may increase, potentially leading to intensified competition among sectors for funding or investment (Wan & Gao, 2010; Zhang & Chen, 2007). This competition tends to reduce the internal synergy within the institution and infrastructure sectors. Concurrently, the diminishing institution-infrastructure synergy may reflect the dual marginal effect of infrastructure investment on both infrastructure growth and the feedback from improved infrastructure on economic growth, which is regarded as an institutional factor (Du et al., 2022). For example, as observed in Fig. 10, the drainage pipeline density (F4) showed a decreasing centrality ranking during the study period, reflecting that there are fewer synergy effects for drainage pipeline construction. This trend may impact the flood control capability in the background of urban expansion. This leads to another issue, the rapid urban expansion in China, which may explain the decreasing agent-infrastructure synergy. The urban infrastructure expansion in China is argued to result in socially excessive infrastructure for residents, making public service and social welfare fall behind urban growth (Dinlersoz & Fu, 2022; Li et al., 2022; Lin et al., 2022). As a result, increasingly more areas of urban regions in China have been exposed to flood risks with vast impervious surfaces, while the social and institutional support to help residents resist and recover from flooding disasters has not kept pace with the speed of infrastructure development, affecting the coordination of flood resilience. These issues underscore the need for urban planners to reconsider infrastructure construction to balance investment tradeoffs, enhance preparedness for flood risks, and better coordinate agent-level

flooding resilience.

It is important to note that this study aggregates all cities into a single sample pool for robust correlation analysis, which does not allow for differentiation at a subnational level. However, the primary aim is to develop and apply an analytical framework at the national scale. Future studies could segment sample cities by geographical location or administrative regions to assess the subnational coupling strength of urban flood resilience.

4.2. Subnetwork level: complex temporal variation patterns

4.2.1. Prominence of the agent component

The correlation network approach also provides insights into synergy and tradeoff effects at the subnetwork level. As shown in Fig. 6, despite a slight decrease in synergy connectivity and efficiency, the agent network consistently exhibits an exceptionally high level of internal synergy across all metrics. It also demonstrates a notably high level of internal tradeoff, particularly when compared to the institution and infrastructure networks. This distinction highlights the agent network's significant role in the overall coupling effect of urban flood resilience.

As discussed in section 4.1, the relatively low synergy levels of the institution and infrastructure components may stem from inter-sector competition for financial resources. Nonetheless, explaining the prominence of the agent component in both synergy and tradeoff aspects is more complex. On the one hand, the high internal synergy within the agent network indicates that agent-level indicators are highly cooperative, with interactions that are mutually beneficial and contribute to cohesive flooding resilience at the agent level. On the other hand, the considerable internal tradeoff suggests competition within the same network, possibly driven by differing priorities and conflicts over resource allocation among several indicators. For example, multiple notable tradeoff effects are found between Per capita loan balance (A6) and other indicators, such as the Unemployment insurance coverage (A12) and Per capita deposit balance (A7). This observation suggests that the decision-makers should balance between promoting loan rates, which are argued to contribute to economic growth (Nguyen et al., 2023), and other public policies that are essential for agent-level urban flood resilience. Nonetheless, the connectivity gap between the synergy and tradeoff networks is approximately 0.1, indicating that the synergistic effects still significantly outweigh the tradeoff effects.

Fig. 7 (a) shows that the links between the agent and institution components, as well as those between the agent and infrastructure components, have the highest adjusted densities among all inter-subnetwork links in the synergy network. This observation further reveals that the agent component effectively cooperates with the institutional and infrastructure components. This observation can be viewed as indicative of the effectiveness of China's governance in aligning economic development and urbanization with the well-being of its citizens across various socio-economic fields (Ye et al., 2014). Chen (2018) notes that current Chinese urban governance embraces the principles of "people-centred development" and a "community of shared spatial interests" in urban risk management. These principles aim to better integrate the community and citizens in developing urban risk resilience (Yu et al., 2024), which can contribute to the high levels of observed internal and external synergies in the agent components. The Flood Control Law of the People's Republic of China (2016) also underlines the importance of citizen-inclusive flood prevention and management, including flood-prevention education, controlling population growth in flood retention regions, and supporting the development of flood insurance. The General Office of the State Council of China (2021) also restated that urban flood management and resilience development should be people-centred.

Noticeably, similar to the overall trends observed in section 4.1, the synergy strength between the agent and institution components, as well as between the agent and infrastructure components, has decreased over the study period. In comparison, the tradeoff effect between the agent

and infrastructure components has slightly increased after 2020. The efficiency of the agent synergy network has also experienced some decline. These temporal variations suggest that while the synergy within the agent component remains strong, proactive government planning is necessary to prevent further decoupling.

4.2.2. Increasing social-environment tradeoff: a positive signal

It is important to clarify that the indicators used in this study do not capture the temporal change of attributes in the urban ecosystem. Instead, they are chosen solely to quantify the naturally endowed flood risks and the environmental aspects of flood risk. Thus, the human-environment coupling reflected in our analysis indicates society's response to potential flood risks rather than the state of environmental protection.

Fig. 7 shows that inter-subnetwork connections among the agent, institution, and infrastructure components generally exhibit the highest synergy density and lower tradeoff density. Conversely, the environment-agent and environment-infrastructure links display the lowest synergy strength and the highest tradeoff density. Furthermore, their adjusted density in the tradeoff network has notably increased during the study period. Meanwhile, the environment-institution links show a slightly rising tradeoff density with medium synergy strength. This pattern indicates that synergy between the environment and other components is limited, and the tradeoff effect is becoming increasingly significant. However, this could be interpreted as a positive signal.

The high strength and rising trend of the tradeoff effect suggest a counterintuitive perspective that the flood resilience components of agents, institutions, and infrastructure are effectively aligned with naturally endowed flood risks, and this alignment is improving. This interpretation emerges from our analytical method, where we employed a $(1-x)$ conversion on indicators E2, E3, and E4, which initially contribute negatively to flood resilience. As explained in section 2.4, this conversion was applied so that higher values of these indicators represent lower natural flood exposure. Therefore, for inter-network links connecting to these nodes, a tradeoff (negative) connection actually implies that lower flood exposure is associated with lower social resilience. In essence, our findings indicate that cities facing higher natural flood risks are better prepared, demonstrating higher socio-economic preparedness, which leads to a more effective risk-resilience match. Existing studies report China's urban flood resilience mismatches with natural-endowed and socio-economic-induced flood exposure. Urban areas with high flood exposure have not always had correspondingly high levels of resilience, leading to exacerbated flood damage (Song et al., 2019; Yang et al., 2021). Combined with these studies, the insight of our study suggests a possibility that the observed mismatch may exist mainly between the resilience and socio-economic elements of risk exposure instead of the environmental flood exposure. This could help narrow the focus of policies and future studies, directing them to better match flood resilience with the socio-economic aspects of flood risk rather than focusing solely on the environmental dimension. Moreover, the observed matching trend may be connected to the effectiveness of the national flood management policies in the 2010s, which focused on cities vulnerable to flood threats, enhancing their management capabilities and prioritizing resource allocation towards them (Flood Control Law of the People's Republic of China, 2016; National Development and Reform Commission of China, 2016). This may reduce the financial tradeoffs and increase the infrastructure and institutional synergies in the cities with high natural flood risks. Still, more robust statistical analysis in future studies is required to verify this hypothesis.

Furthermore, this risk-resilience matching cannot fully account for trends associated with human activities. Regarding E1 (vegetation coverage in non-built-up areas), further discussion is warranted. Urbanization can enhance infrastructural and institutional flood resilience (Yang & Wang, 2024) but may reduce natural grassland and forest coverage, thus increasing flood exposure at the same time (Luo & Zhang, 2022). Consequently, as urbanization progresses, the tradeoff between

the environment and other social components may also intensify. Policymakers should, therefore, also focus on mitigating damage to natural vegetation, mainly deforestation caused by urbanization. By implementing related measures, it may be possible to reduce natural flood risks moderately.

Regarding the framework design, the environment component is unique in that some of the low inter-subnetwork synergy and high tradeoffs can signal positive implications. This distinctive characteristic further justifies our EIFA framework design, in which the environment sector is structured independently from the urban system. Notably, while the inter-subnetwork connections reflect only subnetwork-level interactions, further research could explore this in-depth by differentiating the tradeoff links. Specifically, it would be beneficial to separate the links connecting to E1, which adhere to the standard definition of tradeoff, from those connecting to the other three environment indicators because these latter links indicate a positive risk-resilience match. This practice can help better segregate the two diverse implications.

4.3. Node level: the core role of agents

Network analysis offers a distinct advantage over other methods for analyzing coupling effects, as it allows for a detailed focus on individual variables. Calculating centrality and detecting hubs are major approaches at the node level. These methods elucidate the importance of each node and reveal the key nodes within the network. As shown in Fig. 9, nodes A7 (Per capita deposit balance) and A12 (Unemployment insurance coverage) consistently act as synergy hubs. Node A11 (Medical insurance coverage) also frequently serves as a hub, with only two exceptions when node A5 (Per capita retail sales) took its place. Given that A5 was a hub only twice during the study period, and A11 was consistently a hub after 2014, it is clear that A7, A11, and A12 are central to the synergy effects of China's urban flood resilience.

The importance of deposit balance as a factor in individual-level risk resilience is well-documented (Büyükoğuzkan et al., 2022; Huang et al., 2024; Jaafari et al., 2024). Our findings reinforce this viewpoint. This suggests that maintaining a certain level of savings can effectively and comprehensively enhance individual flood resilience. Regarding economic policy, governments are recommended to consider incentivizing savings among residents rather than focusing solely on stimulating consumption to harness the synergy effects of savings.

Furthermore, among the three types of insurance coverage analyzed, medical and unemployment insurance stands out as hubs. Medical insurance not only facilitates swift coverage of post-flood medical services but also helps alleviate stress among the affected populations, potentially reducing psychological issues (Mulchandani et al., 2019). The relevance of unemployment insurance is also highlighted by studies showing that unemployment rates often increase following flood events (Sarmiento, 2007; Sun et al., 2022; Xiao et al., 2013). Therefore, extensive unemployment insurance coverage can be important in improving post-flood resilience. These results suggested that the insurance policies can prioritize medical and unemployment insurance because the increase of the medical and unemployment insurance coverages, which are two synergy hubs, can exert more synergy effects than other types of insurance and provide a more cost-effective flood resilience improvement.

Additionally, citizen participation is increasingly recognized as crucial in developing smart cities, where infrastructure and institutional developments alone are insufficient (Xu & Zhu, 2021; Yu et al., 2024). Our study supports this perspective, as among the smart city-related nodes (I6, I17, I19, F17, A8, and A9), A8 and A9 exhibit the highest average centrality. Policymakers are advised to adhere to a people-centered approach in smart city initiatives (Chen, 2018; Yu et al., 2024) and effectively leverage the agent component's central role. This focus can optimize the synergy effects of China's urban flood resilience, enhancing the overall resilience framework.

5. Conclusion

Urban flood resilience is an emerging important topic in urban sustainability research. China's cities grapple with escalating flooding threats. Understanding the coupling effects, including synergy and tradeoff effects, can help decision-makers design well-informed resilience policies and improve urban flood resilience cost-effectively. However, current studies lack a large-scale and long-term analysis of the coupling effect of urban flood resilience in China. In terms of methods, as a helpful tool to understand coupling effects from multiple aspects, correlation network analysis has not been applied in the field of urban flood resilience. In that sense, this study first develops an updated conceptual framework for urban flood resilience. It then revised current correlation network analysis methods based on the framework. Finally, utilizing this framework, it investigated the coupling effect of urban flood resilience in China from 2012 to 2022.

In terms of the study implications, we introduced several updated metrics to enhance network analysis for the coupling effect of urban flood resilience. Throughout the period from 2012 to 2022, we constructed eleven networks to analyze the evolving coupling effect within China's urban systems. The findings indicate a general trend of decoupling in synergy alongside increased tradeoff links, mainly driven by interactions involving infrastructure and institutional components. As for the subnetworks, the agent component of the network displayed robust internal and intra-network coupling, with synergy consistently outweighing tradeoffs. This suggests an effective governmental focus on aligning resilience development in other components with societal well-being, reflecting a people-centered approach in urban governance. In addition, an increasing socio-environmental tradeoff was identified as a potentially positive development, indicating an improved alignment between environmental flood risks and urban flood resilience strategies. At the node level, agent-related nodes emerged as particularly influential, reflecting the importance of individual-level economic stability and comprehensive insurance coverage in enhancing flood resilience.

Despite its findings, this study acknowledges several limitations, including the absence of subnational-level analysis and the need for further validation of the resilience-risk match observed. More granular studies at the subnational level could provide deeper insights into localized urban flood resilience strategies. Additionally, future research can consider separating tradeoff links connected to specific environmental indicators to refine our interpretation of the human-environment tradeoff effect. Moreover, with our updated analyzing framework and method, further studies can focus on other areas with various spatio-temporal spans.

This study has three major contributions, including a revised theoretical framework for understanding the coupling effects of urban flood resilience, an updated network analysis paradigm based on the framework, and the quantification of the long-term coupling effect and its temporal variation of Chinese urban flood resilience. The EIFA framework we proposed provides a novel taxonomy of urban flood resilience components. This approach reveals the previously undiscovered resilience-risk matching effects in Chinese cities. Further, the updated correlation network analysis is better tailored for quantifying coupling effects than traditional ones. Empirically, we employed the framework and the network-based approach to discover how synergy and tradeoff effects of Chinese urban flood resilience vary over time. It is not only the first time that network analysis has been adopted in the field of urban flood resilience but also the first long-term and national-level analysis of coupling effects in Chinese urban flood resilience. Based on our findings, urban planners should balance infrastructure investments with tradeoff considerations, enhance coordination between agents and institutions, and focus on socio-economic aspects of flood risk rather than solely on environmental factors. Additionally, promoting savings, expanding unemployment insurance coverage, and prioritizing public participation in smart city initiatives are key to strengthening urban flood resilience.

CRediT authorship contribution statement

Zhang Chen: Writing – original draft, Visualization, Software, Data curation. **Shiyao Zhu:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Haibo Feng:** Validation, Supervision. **Hongsheng Zhang:** Writing – review & editing. **Dezhi Li:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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Data availability

The source data from the China Urban Construction Statistical Yearbooks and China City Statistical Yearbooks is available on the China Yearbook Full-text Database (CYFD) at oversea.cnki.net/kns?dbcode=CYFD. The source data from the remote sensing products is freely available on Google Earth Engine at earthengine.google.com. Python codes for data processing and visualization will be made available on request.

References

- Amirzadeh, M., Sobhaninia, S., & Sharifi, A. (2022). Urban resilience: a vague or an evolutionary concept? *Sustainable Cities and Society*, 81, Article 103853. <https://doi.org/10.1016/j.scs.2022.103853>
- Asad, R., Ahmed, I., Vaughan, J., & Von Meding, J. (2022). Traditional water knowledge: challenges and opportunities to build resilience to urban floods. *International Journal of Disaster Resilience in the Built Environment*, 13(1), 1–13. <https://doi.org/10.1108/Ijdrbe-08-2020-0091>
- Ashouri, H., Hsu, K., Sorooshian, S., Braithwaite, D. K., Knapp, K. R., Cecil, L. D., Nelson, B. R., & Prat, O. P. (2015). *PERSIANN-CDR: Daily precipitation climate data record from multi-satellite observations for hydrological and climate studies*. Bulletin of the American Meteorological Society. <https://doi.org/10.1175/BAMS-D-13-00068.1>
- Bartsch, R. P., Liu, K. K. L., Bashan, A., & Ivanov, P. C. (2015). Network physiology: how organ systems dynamically interact. *PLOS One*, 10(11), Article E0142143. <https://doi.org/10.1371/Journal.Pone.0142143>
- Bedru, H. D., Yu, S., Xiao, X., Zhang, D., Wan, L., Guo, H., & Xia, F. (2020). Big networks: A survey. *Computer Science Review*, 37, Article 100247. <https://doi.org/10.1016/j.cosrev.2020.100247>
- Bertilsson, L., Wiklund, K., De Moura Tebaldi, I., Rezende, O. M., Veról, A. P., & Miguez, M. G. (2019). Urban flood resilience – a multi-criteria index to integrate flood resilience into urban planning. *Journal of Hydrology*, 573, 970–982. <https://doi.org/10.1016/j.jhydrol.2018.06.052>
- Bonacich, P. (1987). Power and centrality: a family of measures. *American Journal of Sociology*, 92(5), 1170–1182. <https://doi.org/10.1086/228631>
- Büyükoğkan, G., Ilıcak, Ö., & Feyzioğlu, O. (2022). A review of urban resilience literature. *Sustainable Cities and Society*, 77, Article 103579. <https://doi.org/10.1016/j.scs.2021.103579>
- Cao, W., Zhou, Y., Güneralp, B., Li, X., Zhao, K., & Zhang, H. (2022). Increasing global urban exposure to flooding: an analysis of long-term annual dynamics. *Science of the Total Environment*, 817, Article 153012. <https://doi.org/10.1016/j.scitotenv.2022.153012>
- Central People's Government of the People's Republic of China. (2009). *Overview of China's administrative divisions*. April 17. Central Government Portal https://www.gov.cn/Test/2009-04/17/Content_1288030.htm
- Chelleri, L. (2012). From the «resilient city» to urban resilience. A review essay on understanding and integrating the resilience perspective for urban systems. *Documents D'analisi Geografica*, 58(2), 287–306. <https://dag.revista.uab.es/article/download/v58-n2-chelleri/pdf-en>
- Chen, J. (2018). Urban risk generalization in China: space and governance. *Social Sciences in China*, 39(4), 79–95. <https://doi.org/10.1080/02529203.2018.1519215>
- Deng, Y., Jiang, Y.-H., Yang, Y., He, Z., Luo, F., & Zhou, J. (2012). Molecular ecological network analyses. *BMC Bioinformatics*, 13(1), 113. <https://doi.org/10.1186/1471-2105-13-113>
- Dinlersoz, E. M., & Fu, Z. (2022). Infrastructure investment and growth in China: a quantitative assessment. *Journal of Development Economics*, 158, Article 102916. <https://doi.org/10.1016/j.jdeveco.2022.102916>
- Dong, Q., Zhong, K., Liao, Y., Xiong, R., Wang, F., & Pang, M. (2023). Coupling coordination degree of environment, energy, and economic growth in resource-based provinces of China. *Resources Policy*, 81, Article 103308. <https://doi.org/10.1016/j.resourpol.2023.103308>
- Du, X., Zhang, H., & Han, Y. (2022). How does new infrastructure investment affect economic growth quality? Empirical evidence from China. *Sustainability*, 14(6), 6. <https://doi.org/10.3390/Su14063511>. Article.
- Faraway, J. J. (2002). *Practical regression and ANOVA using R*, 168. Bath: University of Bath.
- Felipe-Lucia, M. R., Soliveres, S., Penone, C., Fischer, M., Ammer, C., Boch, S., Boeddinghaus, R. S., Bonkowski, M., Buscot, F., Fiore-Donno, A. M., Frank, K., Goldmann, K., Gossner, M. M., Hölzel, N., Jochum, M., Kandeler, E., Klaus, V. H., Kleinebecker, T., Leimer, S., & Allan, E. (2020). Land-use intensity alters networks between biodiversity, ecosystem functions, and services. *Proceedings of the National Academy of Sciences*, 117(45), 28140–28149. <https://doi.org/10.1073/Pnas.2016210117>
- Fenner, R., O'donnell, E., Ahilan, S., Dawson, D., Kapetas, L., Krivtsov, V., Ncube, S., & Vercrussse, K. (2019). Achieving urban flood resilience in an uncertain future. *Water*, 11(5), 1082. <https://doi.org/10.3390/W11051082>
- Flood Control Law of the People's Republic of China. (2016). Beijing, China: National People's Congress. <https://faolex.fao.org/docs/pdf/chn154921.pdf>
- General Office of the State Council of China. (2021). *Implementation opinions on strengthening urban waterlogging control*. The State Council of the People's Republic of China. https://www.gov.cn/zhengce/zhengceku/2021-04/25/content_5601954.htm
- Hagberg, A., Swart, P. J., & Schult, D. A. (2008). *Exploring network structure, dynamics, and function using NetworkX (No. LA-UR-08-05495; LA-UR-08-5495)*. Los Alamos National Laboratory (LANL), Los Alamos, NM (United States). <https://www.osti.gov/biblio/960616>
- Han, S., Wang, B., Ao, Y., Bahmani, H., & Chai, B. (2023). The coupling and coordination degree of urban resilience system: a case study of the Chengdu-Chongqing urban agglomeration. *Environmental Impact Assessment Review*, 101, Article 107145. <https://doi.org/10.1016/j.eiar.2023.107145>
- Hu, B., Li, Z., Wu, H., Han, H., Cheng, X., & Kang, F. (2023). Coupling strength of human-natural systems mediates the response of ecosystem services to land use change. *Journal of Environmental Management*, 344, Article 118521. <https://doi.org/10.1016/J.jenvman.2023.118521>
- Huang, J., Lu, H., Jin, H., & Zhang, L. (2024). Urban resilience in China's eight urban agglomerations: evolution trends and driving factors. *Environmental Science and Pollution Research*, 31(1), 622–633. <https://doi.org/10.1007/S11356-023-30971-1>
- Ings, T. C., Montoya, J. M., Bascompte, J., Blüthgen, N., Brown, L., Dormann, C. F., Edwards, F., Figueroa, D., Jacob, U., Jones, J. I., Lauridsen, R. B., Ledger, M. E., Lewis, H. M., Olesen, J. M., Van Veen, F. J. F., Warren, P. H., & Woodward, G. (2009). Review: ecological networks – beyond food webs. *Journal of Animal Ecology*, 78(1), 253–269. <https://doi.org/10.1111/J.1365-2656.2008.01460.X>
- Jaafari, A., Mafi-Gholami, D., & Yousefi, S. (2024). *A spatiotemporal analysis using expert-weighted indicators for assessing social resilience to natural hazards*, 100. Sustainable Cities and Society, Article 105051. <https://doi.org/10.1016/j.scs.2023.105051>
- Japan Aerospace Exploration Agency. (2021). *ALOS DSM: Global 30m v3.2 [Data set]*. Google Earth Engine. <https://earthengine.google.com>
- Kraemer, H. C., & Blasey, C. (2015). *How many subjects?: Statistical power analysis in research*. Sage publications.
- Kundzewicz, Z. W., Kanae, S., Seneyratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., & Sherstyukov, B. (2013). Flood risk and climate change: global and regional perspectives. *Hydrological Sciences Journal*, 59(1), 1–28. <https://doi.org/10.1080/02626667.2013.857411>
- Latora, V., & Marchiori, M. (2003). Economic small-world behavior in weighted networks. *European Physical Journal B*, 32(2), 249–263. <https://doi.org/10.1140/Epjb/E2003-00095-5>
- Li, L. (2011). The incentive role of creating “cities” in China. *China Economic Review*, 22(1), 172–181. <https://doi.org/10.1016/j.chieco.2010.12.003>
- Li, L., Fan, Z., Feng, W., Yuxin, C., & Keyu, Q. (2022). Coupling coordination degree spatial analysis and driving factor between socio-economic and eco-environment in northern China. *Ecological Indicators*, 135, Article 108555. <https://doi.org/10.1016/J.ecolind.2022.108555>
- Liang, C., Li, D., Yuan, Z., Liao, Y., Nie, X., Huang, B., & Xie, Z. (2019). Assessing urban flood and drought risks under climate change, China. *Hydrological Processes*, 33(9), 1349–1361. <https://doi.org/10.1002/hyp.13405>
- Lin, Y., Peng, C., Chen, P., & Zhang, M. (2022). Conflict or synergy? Analysis of economic-social-infrastructure-ecological resilience and their coupling coordination in the Yangtze River economic belt, China. *Ecological Indicators*, 142, Article 109194. <https://doi.org/10.1016/J.ecolind.2022.109194>
- Luo, K., & Zhang, X. (2022). Increasing urban flood risk in China over recent 40 years induced by LUCC. *Landscape and Urban Planning*, 219, Article 104317. <https://doi.org/10.1016/J.landurbplan.2021.104317>

- Ma, Y., Cui, Y., Tan, H., & Wang, H. (2022). Case study: diagnosing China's prevailing urban flooding—causes, challenges, and solutions. *Journal of Flood Risk Management*, 15(3), E12822. <https://doi.org/10.1111/Jfr3.12822>
- McClymont, K., Morrison, D., Beavers, L., & Carmen, E. (2020). Flood resilience: a systematic review. *Journal of Environmental Planning and Management*, 63(7), 1151–1176. <https://doi.org/10.1080/09640568.2019.1641474>
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2013). *China urban construction statistical yearbook 2013*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2014). *China urban construction statistical yearbook 2014*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2015). *China urban construction statistical yearbook 2015*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2016). *China urban construction statistical yearbook 2016*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2017). *China urban construction statistical yearbook 2017*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2018). *China urban construction statistical yearbook 2018*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2019). *China urban construction statistical yearbook 2019*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2020). *China urban construction statistical yearbook 2020*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2021). *China urban construction statistical yearbook 2021*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2022). *China urban construction statistical yearbook 2022*. China Architecture & Building Press.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2023). *China urban construction statistical yearbook 2023*. China Architecture & Building Press.
- Mulchandani, R., Smith, M., Armstrong, B., Beck, C. R., Oliver, I., Waite, T. D., Beck, C. R., Bone, A., Amlot, R., Kovats, S., Armstrong, B., Leonardi, G., Rubin, G. J., & Oliver, I. (2019). Effect of insurance-related factors on the association between flooding and mental health outcomes. *International Journal of Environmental Research and Public Health*, 16(7), 1174. <https://doi.org/10.3390/ijerph16071174>
- National Bureau of Statistics of China. (2013). *China city statistical yearbook 2013*. China Statistics Press.
- National Bureau of Statistics of China. (2014). *China city statistical yearbook 2014*. China Statistics Press.
- National Bureau of Statistics of China. (2015). *China city statistical yearbook 2015*. China Statistics Press.
- National Bureau of Statistics of China. (2016). *China city statistical yearbook 2016*. China Statistics Press.
- National Bureau of Statistics of China. (2017). *China city statistical yearbook 2017*. China Statistics Press.
- National Bureau of Statistics of China. (2018). *China city statistical yearbook 2018*. China Statistics Press.
- National Bureau of Statistics of China. (2019). *China city statistical yearbook 2019*. China Statistics Press.
- National Bureau of Statistics of China. (2020). *China city statistical yearbook 2020*. China Statistics Press.
- National Bureau of Statistics of China. (2021). *China city statistical yearbook 2021*. China Statistics Press.
- National Bureau of Statistics of China. (2022). *China city statistical yearbook 2022*. China Statistics Press.
- National Bureau of Statistics of China. (2023). *China city statistical yearbook 2023*. China Statistics Press.
- National Development and Reform Commission of China. (2016). *National Flood Retention Area Construction and Management Plan*. National Development and Reform Commission of China. <https://www.ndrc.gov.cn/fggz/fzlgzh/gjjzxgh/201604/P020191104623969573673.doc>
- Nguyen, T. P. T., Trinh, N. T., & Nghiem, S. (2023). Can Chinese banks expand their loan portfolio while maintaining loan quality and profitability post-global financial crisis? *Journal of Chinese Economic and Foreign Trade Studies* (ahead-of-print).
- Sarmiento, C. (2007). The impact of flood hazards on local employment. *Applied Economics Letters*, 14(15), 1123–1126. <https://doi.org/10.1080/13504850600606026>
- Sayers, P., Yuanyuan, L., Galloway, G., Penning-Rowsell, E., Fuxin, S., Kang, W., & Le Quesne, T. (2013). Flood risk management: a strategic approach. <http://hdl.handle.net/11540/81>
- Song, J., Chang, Z., Li, W., Feng, Z., Wu, J., Cao, Q., & Liu, J. (2019). Resilience-vulnerability balance to urban flooding: a case study in a densely populated coastal city in China. *Cities*, 95, Article 102381. <https://doi.org/10.1016/J.Cities.2019.06.012>
- Sorooshian, S., Hsu, K., Braithwaite, D., & Ashouri, H. (2014). *NOAA Climate Data Record (CDR) of precipitation estimation from remotely sensed information using artificial neural networks (PERSIANN-CDR), Version 1 Revision 1*. NOAA National Centers for Environmental Information. <https://doi.org/10.7289/V51V5BWQ>. Retrieved July 27, 2024, from <https://earthengine.google.com>
- Su, W., Ye, G., Yao, S., & Yang, G. (2014). Urban land pattern impacts on floods in a new district of China. *Sustainability*, 6(10), 6488–6508. <https://doi.org/10.3390/Su6106488>
- Sun, J., Zhai, N., Mu, H., Miao, J., Li, W., & Li, M. (2024). Assessment of urban resilience and subsystem coupling coordination in the Beijing-Tianjin-Hebei urban agglomeration, 100. *Sustainable Cities and Society*, Article 105058. <https://doi.org/10.1016/J.ScS.2023.105058>
- Sun, Q., Mann, J., & Skidmore, M. (2022). The impacts of flooding and business activity and employment: a spatial perspective on small business. *Water Economics and Policy*, 08(03), Article 2140003. <https://doi.org/10.1142/S2382624X21400038>
- Tang, X., Huang, X., Tian, J., Pan, S., Ding, X., Zhou, Q., & Sun, C. (2024). A novel framework for the spatiotemporal assessment of urban flood vulnerability, 109. *Sustainable Cities and Society*, Article 105523. <https://doi.org/10.1016/J.ScS.2024.105523>
- Tyler, S., & Moench, M. (2012). A framework for urban climate resilience. *Climate and Development*, 4(4), 311–332. <https://doi.org/10.1080/17565529.2012.745389>
- Wan, D., & Gao, K. (2010). Research on harmony degree of urban infrastructure composite system based on synergy theory. In B. Y. Yi (Ed.), *Proceedings of 2010 International Symposium on Construction Economy and Management (ISCEM2010)* (pp. 200–207). World Acad Union-World Acad Press.
- Wang, P., Li, Y., & Zhang, Y. (2021). An urban system perspective on urban flood resilience using SEM: evidence from Nanjing city, China. *Natural Hazards*, 109(3), 2575–2599. <https://doi.org/10.1007/S11069-021-04933-0>
- Wang, Q., Zhang, R., Li, H., & Zang, X. (2024). Analysis of mechanism and optimal value of urban built environment resilience in response to stormwater flooding. *Ecological Indicators*, 158, Article 111625. <https://doi.org/10.1016/J.Ecolind.2024.111625>
- Wu, H., Hu, B., Han, H., Cheng, X., & Kang, F. (2022a). Network analysis reveals the regulatory effect of mixed stands on ecosystem structure and functions in the Loess Plateau, China. *Science of the Total Environment*, 824, Article 153588. <https://doi.org/10.1016/J.Scitotenv.2022.153588>
- Wu, X., Fu, B., Wang, S., Song, S., Li, Y., Xu, Z., Wei, Y., & Liu, J. (2022b). Decoupling of SDGs followed by re-coupling as sustainable development progresses. *Nature Sustainability*, 5(5), 452–459. <https://doi.org/10.1038/S41893-022-00868-X>
- Xiao, Y., Wan, J., & Hewings, G. (2013). Flooding and the Midwest economy: assessing the Midwest floods of 1993 and 2008. *Geojournal*, 78(2), 245–258. <https://doi.org/10.1007/S10708-011-9415-9>
- Xing, Q., Wu, C., Chen, F., Liu, J., Pradhan, P., Bryan, B. A., Schaubroeck, T., Carrasco, L. R., Gonsamo, A., Li, Y., Chen, X., Deng, X., Albanese, A., Li, Y., & Xu, Z. (2024). Intranational synergies and trade-offs reveal common and differentiated priorities of sustainable development goals in China. *Nature Communications*, 15(1), 2251. <https://doi.org/10.1038/S41467-024-46491-6>
- Xinhua News Agency. (2022). *Investigation report on the "7.20" extraordinary heavy rain disaster in Zhengzhou, Henan released*. January 21. The State Council of the People's Republic of China https://www.gov.cn/xinwen/2022-01/21/content_5669723.htm
- Xu, H., & Zhu, W. (2021). Evaluating the impact mechanism of citizen participation on citizen satisfaction in a smart city. *Environment and Planning B-Urban Analytics and City Science*, 48(8), 2466–2480. <https://doi.org/10.1177/2399808320980746>
- Xu, W., Cong, J., Proverbs, D., & Zhang, L. (2021). An evaluation of urban resilience to flooding. *Water*, 13(15), 15. <https://doi.org/10.3390/W13152022>. Article.
- Xu, X., Wang, M., Wang, M., Yang, Y., & Wang, Y. (2023). The coupling coordination degree of economic, social and ecological resilience of urban agglomerations in China. *International Journal of Environmental Research and Public Health*, 20(1), 413. <https://doi.org/10.3390/ijerph20010413>
- Yamazaki, D., Ikeshima, D., Sosa, J., Bates, P. D., Allen, G. H., & Pavelsky, T. M. (2019). MERIT Hydro: A high-resolution global hydrography map based on latest topography datasets. *Water Resources Research*, 55, 5053–5073. <https://doi.org/10.1029/2019WR024873>
- Yang, T., & Wang, L. (2024). Did urban resilience improve during 2005–2021? Evidence from 31 Chinese provinces. *Land*, 13(3), 397. <https://doi.org/10.3390/Land13030397>
- Yang, Y., Guo, H., Wang, D., Ke, X., Li, S., & Huang, S. (2021). Flood vulnerability and resilience assessment in China based on super-efficiency DEA and SBM-DEA methods. *Journal of Hydrology*, 600, Article 126470. <https://doi.org/10.1016/J.Jhydrol.2021.126470>
- Ye, L., Fan, J., Liang, T., & Jia, D. (2014). Promoting people-centered urbanization: challenges, policies and good governance. In X. Zhu, & S. Zhao (Eds.), *Proceedings Of 2014 International Conference on Public Administration (10th)*, Vol 1 (pp. 394–400). Univ Electronic Science & Technology China Press.
- Yu, L., Li, D., Mao, L., Zhou, S., & Feng, H. (2024). Towards people-centric smart cities: a comparative evaluation of citizens' sense of gain in pilot cities in China. *Journal of Cleaner Production*, 434, Article 140027. <https://doi.org/10.1016/J.Jclepro.2023.140027>
- Yu, S., Yuan, M., Wang, Q., Corcoran, J., Xu, Z., & Peng, J. (2023). Dealing with urban floods within a resilience framework regarding disaster stages. *Habitat International*, 136, Article 102783. <https://doi.org/10.1016/j.habitatint.2023.102783>
- Yuan, M. M., Guo, X., Wu, L., Zhang, Y., Xiao, N., Ning, D., Shi, Z., Zhou, X., Wu, L., Yang, Y., Tiedje, J. M., & Zhou, J. (2021). Climate warming enhances microbial network complexity and stability. *Nature Climate Change*, 11(4), 343–348. <https://doi.org/10.1038/S41558-021-00989-9>
- Zhang, H., & Chen, X. (2007). Fiscal competition and the structure of local public expenditure in China. *Frontiers of Economics in China*, 2(2), 237–249. <https://doi.org/10.1007/S11459-007-0013-1>

- Zhang, J., Wang, Y., He, R., Hu, Q., & Song, X. (2016). Discussion on the urban flood and waterlogging and causes analysis in China. *Advances in Water Science*, 27(4), 485–491. <https://link.oversea.cnki.net/doi/10.14042/j.cnki.32.1309.2016.04.001>.
- Zhou, X., Bai, Z., & Yang, Y. (2017). Linking trends in urban extreme rainfall to urban flooding in China. *International Journal of Climatology*, 37(13), 4586–4593. <https://doi.org/10.1002/Joc.5107>
- Zhu, S., Li, D., & Feng, H. (2019). Is smart city resilient? Evidence from China. *Sustainable Cities and Society*, 50, Article 101636. <https://doi.org/10.1016/j.scs.2019.101636>
- Zhu, S., Feng, H., Arashpour, M., & Zhang, F. (2024). Enhancing urban flood resilience: A coupling coordinated evaluation and geographical factor analysis under SES-PSR framework. *International Journal of Disaster Risk Reduction*, 101, Article 104243. <https://doi.org/10.1016/j.ijdrr.2024.104243>